Discrete Dynamics in Nature and Society

Advanced Quantitative Methods for Financial Markets

Lead Guest Editor: Stefan Cristian Gherghina
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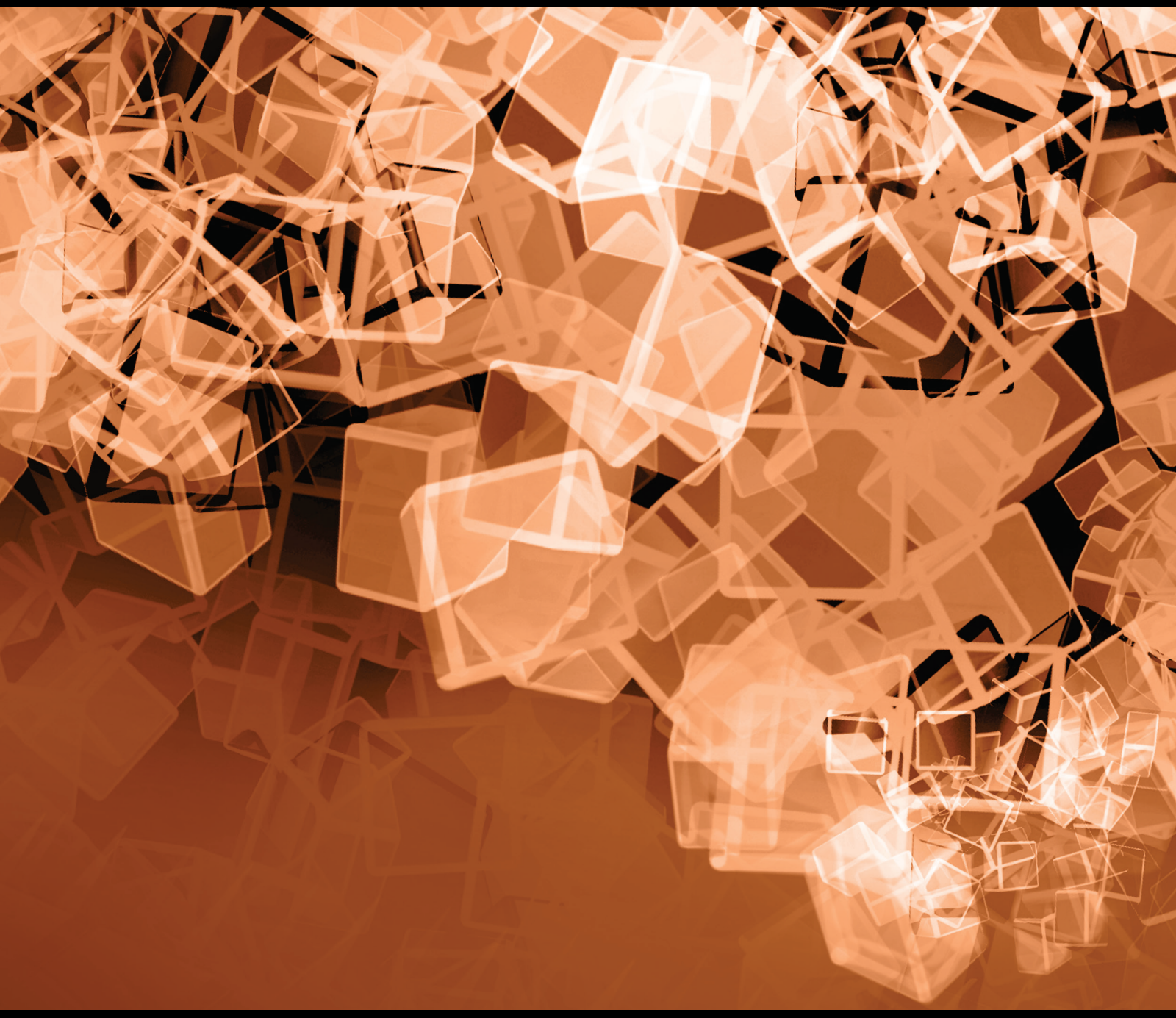

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Research Article

Overflow Effect of COVID-19 Pandemic on Stock Market Performance: A Study Based on Growing Economy

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Purpose. The purpose of this study is to evaluate the effect that COVID-19 has on the performance of the stock market in emerging economies. The findings as a whole demonstrate that the stock market does not react significantly. We believe that the outcomes of this study provide knowledge that is useful for decision makers in financial markets and policy all around the globe. *Methods*. Data for 140 companies are obtained from the official websites of the companies listed on the Pakistan Stock Exchange. The Wilcoxon signed-rank test was used to determine whether there was a significant difference before and after the pandemic era. In addition, the ARDL model was chosen because of the variable integration mix (order 0 and 1). *Implications*. Theoretically, it added to the information that was already available about the implications of the COVID-19 pandemic on the performance of stock markets in emerging economies. In a purely practical way, it will help those in charge of making policies come up with plans to deal with things that cannot be predicted. *Results*. The findings of the analysis demonstrate that the COVID-19 pandemic has caused a 52.85% reduction in the volatility of Pakistan's net profit returns. The study shows a statistically insignificant negative association between the COVID-19 pandemic and Pakistan's stock returns. The empirical results of ARDL models provide the first conclusion of the analysis, indicating that the number of long-term connections was greater than short-term connections. *Conclusion*. According to the findings of the research, the pandemic caused by COVID-19 has a bigger impact on the financial performance of enterprises (both positively and negatively). Some companies are able to maintain their place in the market even if the bulk of the firms see their performance suffer during a pandemic. *Originality*. We are the first to use the ARDL model to evaluate the effect of the new COVID-19 pandemic on a stock market in a developing nation.

1. Introduction

There are numerous factors affecting business performance, including firm size and age [1], internal business processes, innovation strategy, management accounting information [2], liquidity position, asset utilisation and leverage position [3], management competence index [4], exchange rate and inflation rate [5], and COVID-19 [6–8]. Among these elements, the COVID-19 pandemic is the most significant factor affecting the financial performance of businesses worldwide. References [6, 9] explore that the coronavirus illness (COVID-19) has posed a significant threat to both the public and business worlds. COVID-19 began in December 2019 in China, and the entire economic and social worlds are

grappling with this issue [10]. In the year 2020, the World Health Organization officially recognized COVID-19 as a global health emergency [11]. The authors of [6, 11, 12] further stated that COVID-19 had an impact on the average person's life as well as on every business in the world. Business operations ceased and were restricted in compliance with the directives of their respective governments. The experts of the International Monetary Fund indicate that the global gross domestic product will also decrease by 3.2% during the period of 2020 [13]. In short, this pandemic affected the lives of ordinary people as well as the businesses operating around the globe. The business world is also influenced by the financial global crisis before this pandemic in 2007 to 2009 [14]. Mehta's research [15] clearly shows that the financial performance of banking industries falls during the period of an economic crisis. The banks of the UAE were earning two-digit profits before the crisis, but after the crisis, the performance of these banks fell [15]. The results of Mehta [15] show that the profitability measures of return on assets, return on equity, and some other ratios are also decreasing during this global crisis period. The global financial crisis destroyed the business worlds of both the growing economy and the developed economy [16]. Batool and Sahi [16] further stated that the global economy was facing a recession in 2009. Finally, the Organization for Economic Co-operation and Development reported that global trade volume decreased by 13% in 2009 compared to the previous year 2008. Like the global crisis, the COVID-19 pandemic has been harmful to the business world and the financial health of both growing and developed economies is declining [7]. Most governments of developing and developed countries have declared this pandemic period as the economic crisis period [17, 18].

In Pakistan, two main sectors play a vital role in the development of the economy: the service sector and the manufacturing sector [19]. The service sector is a combination of many other sectors, such as education, health, banking, non-profit organizations, and other services [19]. The manufacturing sector includes those firms that process raw materials and convert them into finished goods. The manufacturing sector is a combination of many other industries, such as textiles, food, beverages, tobacco, petroleum, pharmaceuticals, automobiles, fertilisers, chemicals, electronics, leather products, engineering products, tyres, and tubes. The economic development and growth of Pakistan also depend upon the performance of the above-stated sectors. Deitiana and Habibuw [1] describe performance as how companies try to achieve their goals and objectives. The authors further stated that the performance of companies can be measured in three dimensions [1]. These three dimensions are productivity, profitability, and the market value of a company. The Pakistan Stock Exchange's annual report indicates that the KSE100 and KSE30 indices fell in 2019 and 2020. Pakistan's government is also fighting against this pandemic through social distancing and lockdown during the period of COVID-19 [17]. It demonstrates a decline in the companies' financial performance. As a result, organizations must track their financial performance. Before buying or selling a company's stock, an investor must keep in mind the company's financial performance [1]. Every company strives to improve its financial performance to attract more investors. Every company does this by disclosing financial information in the form of financial statements to the general audience. The four most important financial statements are the income statement, the balance sheet, the cash flow statement, and the owner's equity statement, all of which show the company's profitability. In order to draw in additional investors, organizations work to overcome these obstacles and boost their financial performance. Each company has a unique way of measuring its financial results. These methods are Cash Value Added Method (CVA) [20], Technique for Order Preference by Similarity to Ideal Solution Method (TOPSIS) [21], Multi-Criteria Decision-Making Method (MCDM) [22], Data Envelopment Analysis Method (DEA) [23], and Financial Ratios Analysis Method (FRA) [24]. Some other studies like the Financial Ratios Analysis Method (FRA) are used to measure the financial performance, and different statistical tests are used to compare this performance before and during COVID-19. The time period for comparing the performance of different companies is from 2015 to 2020. In this time frame, the first three years from 2015 to 2017 will be considered the pre-COVID-19 period, and the last three years from 2018 to 2020 will be considered the post-COVID-19 period.

However, the performance of companies has been fluctuating from 2015 to 2020. Therefore, it is needed to conduct research that examines financial performance and also identifies factors that affect the financial performance of companies. Hence, the aim of this study is to measure the financial performance of the companies before and during COVID-19. We are also examining the differences between ROA, ROE, CR, DR, and ATR before and during COVID-19. The stated study also contributed to the existing body of knowledge in several ways. First, the research examined the factors that affected the financial performance of companies during the global pandemic crisis. Second, the policy makers adjust their strategies to achieve profitability and improve the financial performance of the companies. Third, the top management hedges this macroeconomic issue in improving the overall financial performance of the companies. Finally, other researchers are needed to expand this research area to other countries. In this study, the research measures the financial performance through ROA, ROE, CR, DR, and ATR and compares the results between pre-COVID-19 and during COVID-19.

This study contributes to the knowledge of stock market performance during a pandemic in developing economies. Usually, the COVID-19 pandemic is considered a disabling dynamic that affects the whole society as well as the firms operating in the economy. This study will focus on the companies that operate in the financial sector and some companies that are performing well and have received a number of government incentives or bailout packages. Furthermore, this study will be concentrated on firms from the main board in order to determine the impact of the COVID-19 pandemic on the biggest listed firms in Pakistan. The contribution of this study is twofold: theoretically, it

adds to the existing knowledge about the effects of the COVID-19 pandemic on stock market performance in developing economies. It will help policymakers in developing policies to deal with uncertain situations.

2. Related Literature Review and Hypothesis Development

The worldwide economy and financial markets have been significantly impacted by the COVID-19 epidemic. From the start of the epidemic, the stock market in particular has seen unparalleled volatility and unpredictability. The spillover impact of COVID-19 on the stock market performance of developing economies is the main topic of this research study. We look at research that assesses the pandemic's impact on the stock market and assesses the numerous elements that affect the overflow effect.

2.1. Studies on Overflow Effect of COVID-19 Pandemic on Stock Market Performance. The effects of the COVID-19 epidemic on stock market performance in developing economies have been the subject of several research studies. For instance, Shehzad et al. [25] examined that the pandemic significantly damaged United States' financial stability as well as the stock market. The authors [25] identified financial instability and disequilibrium in United States' financial market. The effects of the epidemic on the stock markets of Latin American economies were the subject of a different research in [26]. The analysis discovered that while the pandemic had a detrimental effect on the stock markets of all growing economies, it was more pronounced in America. The researchers found that this detrimental effect may have been exacerbated by the ongoing lockdown and travel restrictions in different counties. In addition, a study conducted by [27] examined the potential correlation between government-imposed COVID-19 restriction policies and the administration of COVID-19 vaccines. The study discovered that COVID-19 had a strong influence but a negative impact in pandemic era. The COVID-19 pandemic has had a detrimental effect that has been seen strongly on the international crude oil market as well as the global stock markets, according to research by Yu and Xiao [28]. Finally, Li's analysis in the paper [28] shows that COVID-19 has significant effects on the world financial market. The COVID-19 pandemic brings an unprecedented impact on several aspects, such as stock market performance. Measuring business performance is critical because it influences decision making and the direction in which to improve it [29]. It also plays a vital role in the success of the company. Financial performance describes the financial condition of a company based on predefined goals, standards, and procedures of the company. One way to check the financial performance of a company is to check its economic growth [30]. The authors further stated that economic growth is measured through net profit after tax. In the given study, economic growth is considered as a dependent variable and five independent variables are considered: return on assets (ROA), return on equity (ROE), current ratio (CR), debt ratio (DR), and asset turnover ratio (ATR). The economic earnings have a mutual influence relationship between these variables. Hence, this study examines the impact of the COVID-19 pandemic and also checks whether there is a difference between the pre- and post-pandemic. The investigation is based on the following hypotheses:

H_1: COVID-19 has significant impact on stock market financial performance.

The study of Xu and Banchuenvijit [30] describes that financial performance means the financial condition of a company based on predefined goals, standards, and procedures of the company. Financial performance can be measured through different ratios [31]. Further, Duncan [31] divided these ratios into five different heads, which included liquidity, activity, profitability, debt, and marketability. In each head, we have calculated different types of ratios to measure the financial performance of the company. The profitability of the company is assessed through return on assets (ROA) [32]. High ROA and low ROA indicate how much a company uses its assets to generate revenue. High ROA shows higher profitability, and low ROA shows that the company is not utilising their assets in the best way [32]. The formula to calculate this ratio is net income of the company divided by total assets.

H_2: there is significant difference of ROA between pre-COVID-19 and during COVID-19 pandemic situation.

Return on equity (ROE) measures how much return that the investor will get on their investment [33]. The essential goal of each business is to increase investor wealth by increasing shareholder wealth. Decreasing ROE shows that the shareholders will get out of such a business and also withdraw their investment from such a business. Increasing ROE means an increase in the wealth of the shareholder. The formula to calculate this ratio is net income of the company divided by total equity.

H_3: there is significant difference of ROE between pre-COVID-19 and during COVID-19 pandemic situation.

Furthermore, the authors stated that any company's liquidity can be measured using various ratios such as current ratio, quick ratio, and acid test ratio. Demiroglu and James [34] stated that the liquidity of a company is important because it affects the interest rate determination. If the liquidity position of a company is less than the financial institutions' charge, and vice versa, the liquidity of a company can be formulated through its current assets divided by its current liabilities. A liquidation of the company ranging from 1.5 to 3 will be deemed healthy.

H_4: there is significant difference of CR between pre-COVID-19 and during COVID-19 pandemic situation.

The debt ratio is a measure of the debt or leverage used by the company with respect to total assets [35]. There is a positive relationship between the debt of the company and its profitability [36]. According to the

Irom et al. [37], there is a significant relationship between debt, total assets, and total equity of the company. The result of Damouri et al.'s study [38] shows that leverage of the company will negatively affect the investment decision of the company. Furthermore, they also argue that a high debt ratio indicates that the firm will invest less in capital assets. The result of this ratio can be calculated by total debt divided by total assets. Therefore, another hypothesis was created to see the difference in debt ratio between the pre-COVID-19 and post-COVID-19 periods.

H_5: there is significant difference of DR between pre-COVID-19 and during COVID-19 pandemic situation.

The total asset turnover ratio helps in assessing how much a company is using its assets in generating revenue [33]. The higher the results of the total asset turnover ratio, the better the performance of the company. In their study, Irman and Purwati [33] stated that the higher ratio also indicates that the company is managing its assets in the best way. Therefore, measuring asset turnover is important in assessing business performance. Asset turnover can be measured as the average total assets divided by the revenue of the company.

H_6: there is significant difference of ATR between pre-COVID-19 and during COVID-19 pandemic situation.

3. Materials and Methods

3.1. Study Design. This study is a quantitative type of study because all the values are numeric and collected from the financial statements of the listed companies. A secondary data collection technique was used to collect data from different sources, which included annual reports, related journals, and related articles. The population of the study includes all listed companies on the Pakistan Stock Exchange (PSE) during the period of 2015 to 2020, which included 533 public companies. Arikunto and Suharsimi [39] argue that if the population of the study is a hundred, then the researcher must take all of them. But if the population is over a hundred, then researchers can take around 10% or 20% or 25% or 50% of them. So, the sample was drawn on the basis of Arikunto and Suharsimi's formula [39]. 140 companies were selected. According to the 25%, the companies are $533 \times 25\%$, which is equal to 133.25. These 140 companies are those who have highly contributed to Pakistan's economy.

3.2. Study Model. Figure 1 presents the research model, illustrating the evaluation of a selected company's financial performance pre- and post-COVID-19 using ratio analysis. The figure highlights the comparison between the two periods, emphasizing the presence of a significant difference resulting from the pandemic's impact. Through this model, researchers can assess the company's financial resilience and adaptability to the challenges brought by the global health crisis, providing valuable insights for future decision making.

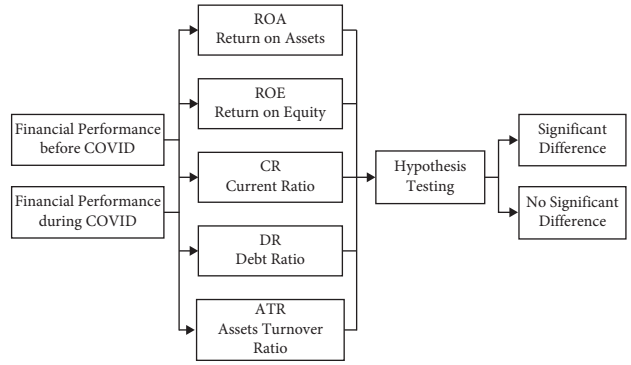

Figure 1: Research model.

3.3. Data Treatment. First, to examine the existence of a long-term relationship between economic growth and ROA, ROE, CR, DR, and ATR, we employ the bound testing approach to co-integration. Second, the autoregressive distributed lag (ARDL) testing procedure is used to establish the long-run impact. Then, descriptive statistics were used for the analysis of the data. Data normality was tested through the Kolmogorov–Smirnov and Shapiro–Wilk tests, and hypothesis testing was tested through the Wilcoxon signed-rank test.

4. Results and Findings

4.1. Descriptive Analysis. Table 1 shows the descriptive statistics of the collected data, which include minimum value, maximum value, mean, and standard deviation for all variables of firms listed on the Pakistan Stock Exchange before and during COVID-19. Based on Table 1, the mean value of ROA is 0.0554 before COVID-19 and 0.0410 during COVID-19. This means that the firm performance of listed firms decreases during the period of a pandemic situation. On the basis of the results, we can say that the COVID-19 pandemic situation is harmful for the listed companies on the Pakistan Stock Exchange. The mean value of ROE was 0.1808 before COVID-19 and 0.0573 during COVID-19. This means that the firm has decreased its equity in the period of a pandemic situation. This decrease also shows that the pandemic situation has positively impacted the company's financial performance. The same way, if we see the current ratios of such a firm, they have also decreased from 2.0268 to 1.8932. But the value of the total debt of the firm increased during COVID-19. Table 1 shows that firms had −0.0043 before COVID-19 and 0.2984 during COVID-19. Last, the asset turnover ratio before COVID-19 was 0.0602, and during COVID-19, it decreased from 0.0602 to 0.0433. This means that the company is not utilising their assets during a pandemic situation due to lockdown. The overall results of the descriptive analysis in Table 1 show that there was a decrease in each of the ratios during COVID-19 as compared to before COVID-19.

4.2. Normality Test. Table 2 shows the results of the Kolmogorov–Smirnov and Shapiro–Wilk normality tests. The overall findings indicate that the distribution of the variable

Table 1: Data descriptive statistics results for all variables before and during COVID-19.

	N	Minimum	Maximum	Mean	Std. Deviation
ROA before COVID-19	140	−1.54	0.56	0.0554	0.17639
ROA during COVID-19	140	−0.37	1.01	0.0410	0.13191
ROE before COVID-19	140	−0.66	1.32	0.1808	0.25036
ROE during COVID-19	140	−6.00	2.45	0.0573	0.63827
CR before COVID-19	140	0.06	16.07	2.0268	2.08144
CR during COVID-19	140	0.10	24.63	1.8932	2.75227
DR before COVID-19	140	−37.22	1.64	−0.0043	3.18886
DR during COVID-19	140	−0.30	16.66	0.2984	1.58328
ATR before COVID-19	140	−1.48	0.52	0.0602	0.17237
ATR during COVID-19	140	−0.37	1.03	0.0433	0.13486
Valid *N* (listwise)	140				

Table 2: Normality test (Kolmogorov–Smirnov and Shapiro–Wilk).

	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
ROA before COVID-19	0.224	140	0.000	0.601	140	0.000
ROA during COVID-19	0.164	140	0.000	0.745	140	0.000
ROE before COVID-19	0.157	140	0.000	0.820	140	0.000
ROE during COVID-19	0.302	140	0.000	0.437	140	0.000
CR before COVID-19	0.240	140	0.000	0.628	140	0.000
CR during COVID-19	0.277	140	0.000	0.431	140	0.000
DR before COVID-19	0.465	140	0.000	0.116	140	0.000
DR during COVID-19	0.378	140	0.000	0.186	140	0.000
ATR before COVID-19	0.211	140	0.000	0.629	140	0.000
ART during COVID-19	0.159	140	0.000	0.752	140	0.000

[a]Lilliefors significance correction.

is not in accordance with a normal distribution, as its value falls below the predetermined significance level of 0.05. The results of each observation shown in Table 2 are less than the significant value of 0.05. Therefore, we cannot test the collected data using a parametric test. Hence, a non-parametric (Wilcoxon signed-rank test) test was used to test the set hypothesis stated above.

4.3. Unit Root Analysis. Prior to discussing various econometric estimation methods such as panel OLS, ARDL, and other econometric tests, it is essential to assess the stationarity of the variables using different panel unit root tests. There are different tests of unit root available such as ADF (Augmented. Dickey-Fuller), PP (Phillips-Perron), Levin in and Chu and IPS unit root tests. Unit root tests are employed to assess the stationarity of a given dataset [40]. The accurate estimation of a data set necessitates the presence of a consistent mean and variance that remains independent over time. Moreover, this condition leads to the classification of the data set as stationary.

Table 3 consists of the results of the LLC test, and the unit root test is applied on variables separately. All variables are stationary at a level, so the order of integration is I (0) and we can suggest that there is no issue of a unit root. But one variable EG is stationary at first difference. Moreover, some variables are significant at 2%, and the remaining are significant at 5% or 10% level of significance.

Table 4 presents the results of the IPS (Im, Pesaran, and Shin) test, and the unit root test is applied on variables separately. All variables are stationary at a level, so the order of integration is I (0) and we can suggest that there is no issue of a unit root. But one variable EG is stationary at first difference. So, these results suggest that ARDL model is an accurate method of estimation because variables are stationary at level.

4.4. Bound Test. Table 5 shows the bound test results. We are using this test to check whether the co-integration between the short run and long run between the variables exists or not. Therefore, looking at the probability values and the F-statistics, the variables may move together in the long run. Ascertain if there actually exists a long-run relationship and, thereafter, calculate the ARDL of the long-run impact. It can be seen from Figures 2 and 3 that the plots of CUSUM and CUSUMSQ statistics are well within critical bounds, implying that all the coefficients in the error correction model are stable.

4.5. ARDL Result of Co-Integration. Co-integration test is used to determine if there is a long-term association between variables. Co-integration was introduced by Nobel laureates Robert Engle and Clive Granger in 1987. Co-integration, unlike correlation, does not assess the long-term movement of two or more data variables. If the F-statistics value is

Table 3: Levin, Lin, and Chu unit root test.

Variable	Level		First difference		Order of integration
	Intercept	Trend and intercept	Intercept	Trend and intercept	
ROA	−3.30*	−3.44**	−7.26*	−7.18**	*I* (0)
ROE	−0.45	−1.93**	−5.57*	−5.63	*I* (0)
CR	−3.43*	−3.35**	−5.16*	−5.11*	*I* (0)
DR	−2.57	−2.93**	−4.09*	−4.03	*I* (0)
ATR	−2.95**	−3.38***	−3.54*	−3.50**	*I* (0)
EG	−0.22*	−0.17*	−6.08***	−6.01***	*I* (1)

H0: indicates the stationary dataset that is the null hypothesis (absence of unit root). Critical values are 10%, 5%, and 2%, and values of LM less than critical values indicate the acceptance of H0 (null hypothesis). This is again the case that the dataset has no unit root. *Significant at 10% level of significance. **Significant at 5% level of significance. ***Significant at 1% level of significance.

Table 4: IPS unit root test.

Variable	Level		First difference		Order of integration
	Intercept	Trend and intercept	intercept	Trend and intercept	
ROA	−3.32*	−3.34*	−8.24*	−8.06*	*I* (0)
ROE	−0.35	−1.93**	−5.58*	−5.69*	*I* (0)
CR	−2.17**	−2.23**	−10.08*	−5.11*	*I* (0)
DR	−2.11	−2.73**	−4.09*	−4.03	*I* (0)
ATR	−3.21**	−3.67**	−3.74*	−3.60**	*I* (0)
EG	−0.32*	−0.29*	−7.01***	−6.09***	*I* (1)

H0: indicates the stationary dataset that is the null hypothesis (absence of unit root). Critical values are 10%, 5%, and 2%, and values of LM less than critical values indicate the acceptance of H0 (null hypothesis). This is again the case that the dataset has no unit root. *Significant at 10% level of significance. **Significant at 5% level of significance. ***Significant at 1% level of significance.

Table 5: Bound test results.

Test statistics	Value	*k*
F-statistics	98.409	5
Critical value bounds		
Significance	*I* (0)	*I* (1)
10%	2.4	3.14
5%	2.43	3.02
2.5%	2.76	3.67
1%	3.36	4.83

below 3, it indicates that there is no co-integration, but F-statistics values over 3 indicate co-relation. Further, the researchers followed the study model of Bhagata and Bolton [41] which suggested a linear association between EG and firm performance. Equation (1) indicates that firm performance in terms of economic growth and other variables of the study.

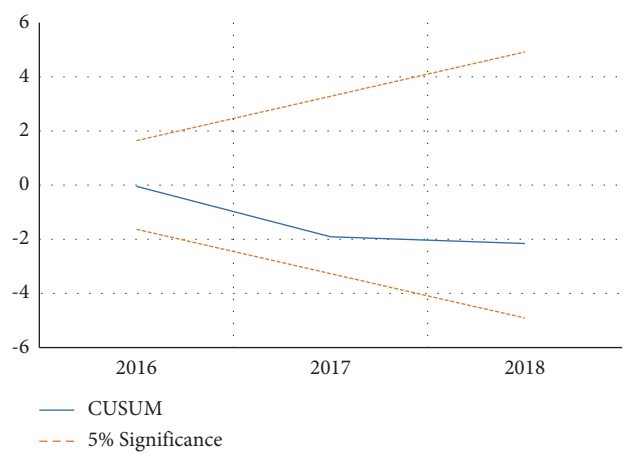

Figure 2: Plot of cumulative sum of recursive residuals.

$$\mathrm{EG}_{(t)j} = \mathrm{ROA}_{(t)j}\beta + \mathrm{ROE}_{(t)j}\beta + \mathrm{CR}_{(t)j}\beta + \mathrm{DR}_{(t)j}\beta + \mathrm{ATR}_{(t)j}\beta + X_{(t)j} + \mu, \quad (1)$$

where $\mathrm{EG}_{(t)}$ is firm economic growth performance for firm j at time t, $\mathrm{CG}_{(t)j}$ is corporate governance measure for firm j at time t, β is the coefficient of all variables measures, X is the vector of some control variables such as firm size and capital structure, and μ represents the error terms. Further, j denotes firms while t is for time. where; $\mathrm{EG}_{(t)j}$ is economic growth to measure the financial performance; $\mathrm{ROA}_{(t)j}$ is return on assets ratio to measure the economic growth; $\mathrm{ROE}_{(t)j}$ is return on equity ratio to measure the economic growth; $\mathrm{CR}_{(t)j}$ is return on equity ratio to measure the economic growth; $\mathrm{DR}_{(t)j}$ is return on equity ratio to measure the economic growth; $\mathrm{ATR}_{(t)j}$ is return on equity ratio to measure the economic growth. The result of co-integration of all variables is as follows.

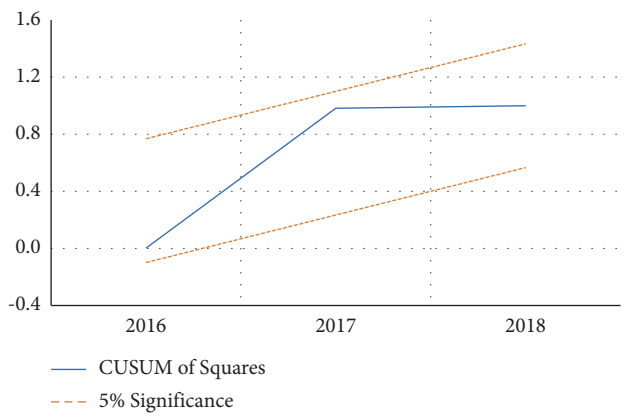

Figure 3: Plot of cumulative sum of squares of recursive residuals (CUSUMSQ).

Table 6: The ARDL result of co-integration.

Variables	AIC lags	F-statistics	Results
EG	2	3.5768	Co-integration
ROA	2	3.5511	Co-integration
ROE	2	10.01171	Co-integration
CR	2	2.9669	No co-integration
DR	2	1.1760	No co-integration
ATR	2	3.76987	Co-integration

Table 6 represents the result of co-integration of all variable in long term. Co-integration is a statistical concept that indicates the long-term relationship between two or more variables. In this context, economic growth has been found to be co-integrated with return on assets, return on equity, and assets turnover ratio, suggesting that these variables move together in the long run. However, the two variables, current ratio and debt ratio, have been identified as those that do not have a co-integration relationship with economic growth. This means that these variables may be independent of economic growth and should be carefully monitored as they may have a different impact on the overall financial health of the organization. Understanding co-integration between variables is crucial for effective financial management and decision making.

The autoregressive distributed lag (ARDL) bound test was applied to estimate the impact of a pandemic on the economic growth of companies. Economic growth is affected during a pandemic. The study employs the autoregressive distributed lag (ARDL) approach; it was introduced originally in [42] and redeveloped as the ARDL bound testing approach in [42, 43]. The ARDL approach is distinguished from other co-integration approaches such as those in [44, 45]. It can be used if the variables are integrated at order one ($I(1)$), order zero ($I(0)$), or a combination of both. The ARDL results of the co-integration model are as follows.

4.6. ARDL Analysis. Due to the mix of stationary and non-stationary variables, the ARDL model was adopted in this research. Through this model, it was feasible to study the relationships that were established in the long and short term. It should be noted in Table 7 that a number of long-term relationships exist between variables rather than short-term ones. In the long run, the COVID-19 pandemic affects economic growth as well as other variables.

Table 7: Long-run and short-run ARDL analysis.

Variables	Coefficients	T-statistics	P value
Long-run coefficients			
ROA	5.6612	2.6708	0.0111**
ROE	−0.3928	−2.4387	0.0195**
CR	1.0965	5.1136	0.0010**
DR	−0.2583	−2.7471	0.0087**
ATR	0.6976	2.8807	0.0076**
C	−25.6866	−4.0475	0.0002**
Short-run coefficients			
ROA	0.1093	0.7597	0.4531
ROE	0.7467	0.2596	0.7968
CR	1.5042	14.5829	0.0010**
DR	−0.0428	−1.0263	0.3126
ATR	0.8722	10.2850	0.0010**
ROA	0.6987	4.7692	0.0010**
C	−0.0034	1.8765	0.0500**

**sign indicate the significance value.

4.7. Non-Linear ARDL Analysis. We applied the "NARDL" in [46] to implement the estimation procedures for the non-linear relationship between the variables over the two periods. The results of estimation are shown in Table 8. The results in this paper suggest that COVID-19 has a negative impact on the return of stock market. As a result, most of the ratios decrease downward. The results can be contrasted with a recent study by Bashir [47], which investigated how oil prices and oil price volatility affect real stock market returns.

4.8. NARDL Wald Test. The result of Wald test shown in Table 9 (also called the Wald chi-squared test) is used to find out whether the explanatory variables in a model are significant or non-significant. The overall results show that DR and ROA are two variables that have significant value.

4.9. Wilcoxon Signed-Rank Test. Tables 10 and 11 show the results of the Wilcoxon signed-rank test and test statistics. The overall results show that 89 listed companies decreased their ROA because they were on negative rank, and 51 listed companies increased their ROA because they were all on positive rank. If we look at the ROE, we see that 103 listed companies decreased because they have a negative rank at the N value of 103 and 37 listed companies increased because they have an N value of 37. Based on the current ratio, 84 companies decrease in said ratio and 56 companies increase in said ratio. Further, in total debt ratio, 95 listed companies were decreasing their debt ratio because they were on negative rank and 45 listed companies were increasing their debt ratio because they were on positive rank. In the asset

Table 8: Long-run and short-run non-linear ARDL analysis.

Variables	Coefficients	T-statistics	*P* value
Long-run coefficients			
ROAt	3.76976	3.9098	0.0013
ROEt	0.38762	2.1409	0.0023
CRt	0.68762	4.7687	0.0010
DRt	−0.1798	−2.7897	0.0018
ATRt	0.09789	5.7692	0.0010
C	−10.9868	−3.8798	0.0012
Short-run coefficients			
ΔROAt	0.0989	1.9864	0.0060
ΔROEt	0.0180	2.5906	0.0045
ΔCRt	1.0099	7.4629	0.0010
ΔDRt	−0.1498	−1.9017	0.0142
ΔATRt	0.0914	4.9890	0.0010
C	−0.0080	2.9001	0.0005

Table 9: NARDL Wald test.

Exogenous	Short-run		Long-run	
	F-stat.	Prob.	F-stat.	Prob.
DR	3.45	0.153	0.786	0.478
ROA	3.90	0.167	3.091	0.005

Table 10: Wilcoxon signed-rank test results.

		N	Mean rank	Sum of ranks
ROA during COVID-19-ROA before COVID-19	Negative ranks	89[a]	77.48	6896.00
	Positive ranks	51[b]	58.31	2974.00
	Ties	0[c]		
	Total	140		
ROE during COVID-19-ROE before COVID-19	Negative ranks	103[d]	72.67	7485.00
	Positive ranks	37[e]	64.46	2385.00
	Ties	0[f]		
	Total	140		
CR during COVID-19-CR before COVID-19	Negative ranks	84[g]	79.31	6662.00
	Positive ranks	56[h]	57.29	3208.00
	Ties	0[i]		
	Total	140		
DR during COVID-19-DR before COVID-19	Negative ranks	95[j]	77.20	7334.00
	Positive ranks	45[k]	56.36	2536.00
	Ties	0[l]		
	Total	140		
ART during COVID-19-ATR before COVID-19	Negative ranks	91[m]	76.77	6986.00
	Positive ranks	49[n]	58.86	2884.00
	Ties	0[o]		
	Total	140		

[a]ROA during COVID-19 < ROA before COVID-19. [b]ROA during COVID-19 > ROA before COVID-19. [c]ROA during COVID-19 = ROA before COVID-19. [d]ROE during COVID-19 < ROE before COVID-19. [e]ROE during COVID-19 > ROE before COVID-19. [f]ROE during COVID-19 = ROE before COVID-19. [g]CR during COVID-19 < CR before COVID-19. [h]CR during COVID-19 > CR before COVID-19. [i]CR during COVID-19 = CR before COVID-19. [j]DR during COVID-19 < DR before COVID-19. [k]DR during COVID-19 > DR before COVID-19. [l]DR during COVID-19 = DR before COVID-19. [m]ART during COVID-19 < ATR before COVID-19. [n]ART during COVID-19 > ATR before COVID-19. [o]ART during COVID-19 = ATR before COVID-19.

turnover ratio, 91 companies are ranked negatively, while 49 are ranked positively. The overall results of the Wilcoxon signed-rank test show that there is a change between the values before and during the COVID-19 shown in Table 3.

5. Discussion

The COVID-19 pandemic had a significant impact on developing country stock market performance. Furthermore,

Table 11: Test statistics.

	ROA during COVID-19-ROA before COVID-19	ROE during COVID-19-ROE before COVID-19	CR during COVID-19-CR before COVID-19	DR during COVID-19-DR before COVID-19	ART during COVID-19-ATR before COVID-19
Z	−4.079[b]	−5.304[b]	−3.592[b]	−4.990[b]	−4.266[b]
Asymp. sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000

[b]Based on positive ranks.

COVID-19 had a detrimental impact on the financial market and crude oil prices in the United States. Several variables influence the negative consequences on developing economies, including spread of the virus, continuous lockdown, social distancing, and strict government policies. In this study, the research focused on the impact of the COVID-19 pandemic on the financial system. Consequently, the COVID-19 outbreaks have significant impacts on various industries, including tourism, textile, energy, banking, and food and beverages. The findings suggest that the pandemic has had a significant negative impact on stock market performance, with the severity of the impact varying between countries. Government policies aimed at controlling the pandemic and supporting the economy can have a significant impact on stock market performance. Overall, this topic is of great significance for investors, policymakers, and researchers as they navigate the economic impacts of the pandemic and develop strategies to mitigate its impact on the stock market.

COVID-19 has great impact on the business world on globe in the period of pandemic. Therefore, the need for this study arises to measure the link between the pandemic and stock market performance [48]. The overall analysis shows that COVID-19 has greater influence on the economic growth of the developing economy. As a result, the economic growth of the country decreases, and it also causes decrease in other ratios of the selected companies. This finding is also consistent with the research conducted by [49–51], which also indicate a mixed influence of the pandemic on the stock performance of different sectors [52]. The paper featured an examination of the link between COVID-19 and the economic growth or financial performance of the stock market in both linear ARDL and non-linear NARDL frameworks, as suggested by Shin et al. [46]. The findings and results of models suggest that stock market has downward movements [53]. The impact of COVID-19 on the developing economy was examined in this study. The 2nd hypothesis is that the ROA (return on assets) was confirmed on the basis of the results of the study. Most industries are decreasing their ROA during the period of this pandemic, but a few industries, like engineering, technology, communication, and textiles, are increasing their return on assets. The main reason behind this increase in ROA during this pandemic is that the industries are running and the restrictions set by the government have not affected these industries. The result of this study is in line with the study that found that the ROA decreased during the period of COVID-19. Meanwhile, the next hypothesis about the ROE and the CR is confirmed because there is a difference between the values of ROE and CR before and during COVID-19. The overall analysis and the results are aligned with the previous study of Yu and Xiao [28] that showed that there is a difference between the values of ROE and CR before and after the decline in oil production. The last two hypotheses are about the leverage (DR and ATR) of the company. This is also accepted because DR and ATR decreased during the period of COVID-19. The statistical results of DR and ATR show that financial performance varies before and during COVID-19. However, the results of this research are consistent with the study conducted by [7], which similarly examined nine sectors in the Indonesian economy. The study's findings assist policymakers in formulating policies in the event of a COVID-19 pandemic as well as investors in making investment decisions. This research is also beneficial to the government, as the government can grant tax benefits to these enterprises that qualify for tax incentives under COVID-19. Additionally, the study's overall conclusion suggests that while the majority of businesses are reducing their performance, some are not. Companies in the food and personal care product, pharmaceuticals, technology, and communication industries continue to perform well despite the COVID-19 pandemic situation, as these companies do not shut down. Government policies (closure, social isolation, etc.) have little effect on such industries. Further, the study has some limitations, like the government's bailout package in the COVID-19 pandemic. In March and April 2020, the government gave bailout packages to the construction industry, which improved the financial performance of this sector. However, the majority of sectors are declining in performance because of the sudden shock of the pandemic. Another reason for the declining performance of companies is the growing economy of the country. Additionally, on April 4, 2020, the Securities and Exchange Commission of Pakistan (SECP) gave instructions to NBFCs, non-bank finance companies, and NBMFCs, non-bank microfinance companies, to grant an extension of one year for their borrowers in repayment of their lending amount. This also improves the performance of NBFCs and NBMFCs.

6. Conclusion

Our overall study and results can be concluded with two findings. First, the COVID-19 pandemic has significant negative effects on stock markets, i.e., decreasing returns and increasing volatility. Second, it will also decrease the overall productivity of the developing economy. As a result, there is a decline in the performance indicators ROA, ROE, CR, DR, and ATR. The results show that, in the long run, the COVID-19 pandemic has a positive impact on economic growth. The study was limited by a lack of financial and economic data for the recent years of 2015 and 2020. The main focus of this study is to investigate the financial performance before and after COVID-19 for the above said period. Another limitation of the study is that we have considered only COVID-19's effect on organization's performance. But other factors like inflation, interest rate, and government bailout packages are also affecting the organization's performance. However, further research should be conducted by considering the said factors with different time frames.

Data Availability

Publicly available datasets were analysed in this study. Most of the data were collected from https://financials.psx.com.pk/ as well as the official websites of the selected companies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Time-Frequency Volatility Spillovers among Major International Financial Markets: Perspective from Global Extreme Events

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In the context of the gradual intensification of the Russia-Ukraine conflict and the continuous spread of the COVID-19 pandemic, this paper concentrates on the impact of global extreme events such as the COVID-19 pandemic and the Russia-Ukraine conflict on the risk spillovers among major international financial markets. First, to measure the impact of the extreme events the on the volatility spillovers among major international financial markets in the time-frequency domain, we combine the TVP-VAR-based connectedness method and BK frequency connectedness approach and focus on the total, directional, and net volatility spillovers. Second, the network visualization method is applied to outline the structural change in the risk contagion, paths, and roles among international financial markets during different periods of global extreme events. The empirical results indicate that the risk spillovers (total, directional, and net spillovers) among international financial markets and the roles played by each market in the process of risk contagion have changed significantly in different periods of global extreme events. Furthermore, volatility spillovers among international financial markets are driven mainly by the high-frequency component (short-term spillovers) during the full sample time. However, the effects of the extreme events also persist in the medium and long terms. Our findings may help understand the dynamics among international financial markets under extreme shocks and provide significant implications for portfolio managers, investors, and government agencies in times of extreme events.

1. Introduction

With the development of economic globalization, the integration process of financial markets is advancing. Although global economic integration has brought certain positive effects on international financial markets, speeding up the speed of information transmission, reducing the cost of market transactions, widening the access to financial assets, and improving the efficiency of global capital allocation [1]. However, financial activities between countries and markets penetrate and influence each other, and fluctuations in one financial market may affect the volatility of another financial market, that is, volatility spillover effects.

In recent years, we have witnessed several domestic and international financial extremes, such as the "International Financial Crisis" in 2008, the "European Debt Crisis" in 2011, the "China Stock Market Crash" in 2015, and the "China-US Trade Friction" in 2018. The shocks from these events have caused huge losses in the global financial markets. However, the international community is currently experiencing the double blow of the spread of the COVID-19 pandemic and the outbreak of the Russia-Ukraine military conflict. The uncertainty of global economic policies has risen sharply. It is difficult for financial markets to be immune to extreme events during a crisis period. Financial market fluctuations or risk transmission will be a more obvious and severe resonance phenomenon. An increasing number of scholars have also begun to pay attention

to the contagion effect between financial markets, and there is a coordinated development trend [2]. Accurate understanding and effective identification of spillovers and related transmission mechanisms among financial markets are beneficial to mitigating financial risks across markets, countries, and regions. Relevant studies on information spillover effects are classified by Hong et al. [3] in terms of mean, volatility, and extreme risk, which are mean spillover effects [4, 5], volatility spillover effects [6, 7], and risk spillovers [8–10]. Tai [11] validates and measures the contagion of the 1997 Asian financial crisis from the stock market to the foreign exchange market. Bekaert et al. [12] analyze the contagion effect of the 2007 financial crisis. The study finds that the contagion effect was relatively lower in the US and global financial markets, while the contagion effect was more pronounced within countries. Trabelsi and Hmida [13] empirically test the market contagion effect in Greece and six European countries during the US subprime mortgage crisis. Wang and Zhang [14] find a significant increase in the spillover between the US and Chinese stock markets after the subprime mortgage crisis.

Extreme events hugely impact global financial markets, and the linkages between the markets also fluctuate [15]. Shah and Dar [16] examine extreme events during periods of market uncertainty; driven mainly by shorter time horizons, the level of cross-market spillovers is high. Several studies have demonstrated that the COVID-19 pandemic triggers changes in the degree of spillover between markets [17–23]. Aldawsari and Alnagada [24] find that the severity of COVID-19 affects the change in volatility of the US stock market. So et al. [25] construct a dynamic financial network based on stock returns, study the network linkages between the COVID-19 pandemic and the Hong Kong financial markets, and find a significant increase in network connectedness due to the outbreak. Zhang et al. [15] show that the COVID-19 pandemic impacts global financial markets, and the connectedness among markets appears to be differentiated. Bissoondoyal-Bheenick et al. [26] find a stronger association between stock returns and risk volatility as the duration of the outbreak increases. Pata [27] examines the relationship between the number of confirmed cases of the COVID-19 pandemic and the number of deaths in the G7 stock markets and finds that the COVID-19 pandemic harms all seven stock markets. Also, during the COVID-19 pandemic, Haddad et al. [28] and Kargar et al. [29] found severe liquidity problems in the bond market. Fasanya et al. [30] examined volatility spillovers between the COVID-19 pandemic and international exchange rate markets. Arif et al. [31] explored the time-frequency link between green and traditional financial markets during the COVID-19 pandemic; the results suggest that financial stability will be an essential factor in determining a smooth transition to green investments. Wang et al. [32], examining intermarket spillover effects, find that the largest intermarket fluctuations from the COVID-19 pandemic outbreak to the present occurred in March 2020 when the epidemic outbreak began. Naeem et al. [33] explore the volatility spillovers between markets during the COVID-19 pandemic and other economic periods of high uncertainty and the return spillover effects between sustainable and Islamic investments worldwide. Costa et al. [34] argue that the risk spillover in the US financial market increases with the epidemic outbreak. Due to the measures to prevent the spread of the epidemic, such as staying at home during the pandemic, which prevented all personnel from going out of the office during the closure, industrialized economic activities were at a standstill, causing the price of oil to fall sharply due to the shrinking global demand, with the average price of oil in the USA in 2020 at $39.68, setting a new 15-year record low with an annual decline of 20.64%. Umar et al. [35] focus on the impact of the Russia-Ukraine conflict on global financial markets and explore the dynamic linkages between important global stock and commodity markets through time-frequency analysis. Su et al. [36] examine the price linkages in energy markets under the role of the COVID-19 pandemic and the Russia-Ukraine conflict. Considering that Russia plays an essential role in the global energy market, the Russian-Ukrainian conflict may lead to risky changes in the commodity markets of oil and natural gas, the primary commodities it exports. Besides, the negative impact of extreme events such as the financial crisis on the world economy will lead to an upward trend in the price of gold. The main reason for the considerable risk response of oil, gold, and natural gas financial markets to extreme events is that oil is a highly volatile commodity [37]. Gold is a safe-haven asset [38] since investors usually use oil and gold as an asset portfolio to hedge their investment risk and achieve a reasonable allocation of their property. And natural gas is a clean and efficient fundamental energy source with high external dependence on the market supply and demand pattern [39]. Therefore, the gold, oil, and natural gas market are essential for the strategic decisions of investment groups, and the gold, oil, and natural gas market have a close connection with each country's stock market.

During this extreme event outbreak, how to accurately measure the changes among financial markets and identify and measure the spillover effects of time-frequency fluctuations among major international financial markets will help policymakers implement strategic plans as well as help investors and creditors analyze market behavior and minimize economic losses arising from the outbreak of extreme events. This study aims to examine how extreme events such as the spread of the global COVID-19 pandemic and the outbreak of the Russia-Ukraine military conflict would affect the dynamic spillovers of financial markets in six countries, including the United States, the United Kingdom, Japan, Germany, France, and China, as well as gold, oil, and natural gas to enrich the literature on risk contagion effects in financial markets. To this end, the time-varying connectedness and frequency connectedness among major international financial markets are explored based on the DY combined with the TVP-VAR model and the BK model.

The main contributions of this paper are as follows:

(1) In the context of the escalating Russia-Ukraine military conflict and the continuous spread of the global COVID-19 pandemic, we innovatively explore the impact of the multiple extreme events of the COVID-19 pandemic combined with the Russia-

Ukraine military conflict on the risk spillover of major international financial markets.

(2) We measure the volatility spillover effects of major international financial markets under the time-frequency model from static and dynamic perspectives, respectively; in the static spillover analysis, we innovatively classify all samples into three special periods (before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict) and deeply explore the impact of extreme events on the volatility spillover relationship major international financial markets.

(3) Based on the DY model, we innovatively combine the reason for employing the two approaches in this study. First, there are some shortcomings of using the rolling-window VAR-based connectedness method: (i) the size of the rolling window needs to be set arbitrarily, (ii) some observations are lost, and (iii) it is sensitive to the presence of outliers. Hence, by combining the TVP-VAR connectedness method and the BK method, we can explore the volatility spillovers among major international financial markets both in the time domain and frequency domain. Besides, we can also overcome the shortcomings of the rolling-window VAR-based BK connectedness method in many ways: (i) it overcomes the burden of the often arbitrarily chosen rolling-window size that could lead to very volatile or flattened parameters; (ii) it avoids the loss of valuable observations; and (iii) since it is based on a multivariate Kalman filter, it is less sensitive to the presence of outliers and thus adjusts immediately to events (Antonakakis et al. [40] and Gabauer and Gupta [41])). By combining the TVP-VAR model and BK model to explore the time-varying connectedness and frequency connectedness among major international financial markets both from the perspective of the time domain (time-varying) and frequency domain (short-term, medium-term, long-term) respectively, which helps to capture the dynamic evolution of risk contagion relationships among major global financial markets from a broader perspective, and thus effectively identify the risk contagion roles (risk exporters and risk receivers) played by each financial market at different times and frequencies.

The rest of the paper is organized as follows: the second part is the descriptive statistics of the sample data; the third part is the description of the research methodology; the fourth part presents and discusses the empirical results; the fifth part is the robustness check; and the last part draws the conclusions.

2. Sample Data

To explore the spillover effects of time-frequency volatility in major international financial markets based on the perspective of extreme events, the following stock indices are chosen: MSCI-France (France), MSCI-Germany (Germany), MSCI-Japan (Japan), MSCI-UK (United Kingdom), MSCI-USA (USA), and MSCI-China (China). Specifically, we choose MSCI-Japan and MSCI-China to represent Asian stock markets; MSCI-USA to represent the US stock markets; and MSCI-France, MSCI-Germany (Germany), and MSCI-UK to track the European market. Furthermore, the summation of the market capitalization of these countries accounts for more than 70% of the global stock market value [42]. We also include oil (WTI spot) and gold (XAU) as the most commonly traded commodities. The data is sourced from Wind Information on a daily frequency ranging from January 2019 to May 2022. To achieve the study aims, we split the sample data into three phases: before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict, with two cutoff dates (23 January 2020 (according to Ashraf [43], our sample data starts from the day (23 January 2020) when the COVID-19 event caught the public eye and databases started reporting the COVID-19-related information) and 21 February 2022). The descriptive statistics for all the selected price returns are reported in Table 1, which exhibit serial correlation, non-normality of distribution, and stationarity of all series. The volatility series are calculated by the GARCH (1, 1) model since the GARCH (1, 1) model is widely used in estimating the volatility of variables [44, 45].

3. Methodology

3.1. TVP-VAR-Based Time-Varying Connectedness Approach. To explore the time-varying volatility spillovers among major global financial markets, we use the TVP-VAR methodology of Koop and Korobilis [46] and combine it with the DY method of [47]. This framework extends the original DY method by allowing the variances to vary over time via a Kalman filter estimation with forgetting factors. The Kalman filter algorithm is employed with forgetting factors chosen based on a Bayesian model selection, as introduced by Koop and Korobilis [46] and demonstrated in Antonakakis et al. [40].

Therefore, the TVP-VAR-based connectedness approach overcomes the shortcomings of using rolling window estimation in the VAR-based connectedness method [40, 41, 48, 49]. By doing so, this method improves the rolling-window VAR-based DY connectedness method in many ways: (i) it overcomes the burden of the often arbitrarily chosen rolling-window size that could lead to very volatile or flattened parameters; (ii) it avoids the loss of valuable observations; and (iii) since it is based on a multivariate Kalman filter, it is less sensitive to the presence of outliers and thus adjusts immediately to events (Antonakakis et al. [40] and Gabauer and Gupta [41]).

According to the Bayesian information criterion (BIC), the TVP-VAR (1) model can be written as follows:

Table 1: Descriptive statistics.

	Mean	Median	SD	Skew	Kurtosis	LB test	JB test	ADF
USA	0.0006	0.0009	0.0146	1.0581	18.8107	214.62***	8693.95***	8.2276***
UK	0.0001	0.0008	0.0148	1.0582	19.2151	38.826***	9136.44***	29.2390***
JPN	0.0001	0.0003	0.0116	0.0124	7.2957	23.051**	630.49***	28.5190***
GER	0.0001	0.0008	0.0156	0.8347	19.3398	27.478***	9217.30***	28.1852***
FRA	0.0003	0.0009	0.0156	1.0361	17.6927	28.629***	7522.44***	28.4149***
CHN	0.0000	0.0004	0.0164	0.2869	10.0911	22.803**	1729.29***	26.0386***
Oil	0.0010	0.0020	0.0277	0.6767	14.5075	83.656***	4587.00***	39.3932***
Gold	0.0004	0.0011	0.0097	0.7094	6.7434	22.631**	547.55***	26.8155***
Gas	0.0268	0.0200	0.0257	2.2037	10.5218	177.06***	2593.61***	8.5760***

Note. ***, **, and * denote the null hypothesis rejection at 1%, 5%, and 10%, respectively.

$$\begin{cases} Y_t = \beta_t Y_{t-1} + \varepsilon_t, \\ \varepsilon_t \sim N(0, S_t), \end{cases} \quad \begin{cases} \beta_t = \beta_{t-1} + \upsilon_t, \\ \upsilon_t \sim N(0, R_t), \end{cases} \quad Y_t = \sum_{j=0}^{z} A_{jt}\varepsilon_{t-j}, \tag{1}$$

where Y_t, Y_{t-1}, and ε_t are $N \times 1$ dimensional vectors. The parameters β_t, υ_t, and S_t are $N \times N$ dimensional matrices, whereas R_t is an $N^2 \times N^2$ dimensional matrix.

After estimating the time-varying coefficients and variance-covariance matrices, we need to transform the TVP-VAR to a TVP-VMA using the Wold representation theorem in (1). Next, using the generalized impulse response functions (GIRFs) that represent the responses of all variables under a shock in variable i, the impact of a shock in variable i on all other variables can be estimated. Since we do not have a structural model, the differences between an h-step ahead forecast with variable i is shocked and not shocked should be computed. The differences can be accounted to the shock in variable i, which can be calculated as follows:

$$\begin{cases} GIRF_t(h, \delta_{j,t}, F_{t-1}) = E(Y_{t+h} \mid \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+h} \mid F_{t-1}), \\ \Psi^g_{j,t}(h) = \dfrac{A_{h,t}S_t\varepsilon_{j,t}}{\sqrt{S_{jj,t}}} \dfrac{\delta_{j,t}}{\sqrt{S_{jj,t}}}, \\ \delta_{j,t} = \sqrt{S_{jj,t}}, \\ \Psi^g_{j,t}(h) = S^{-1/2}_{jj,t} A_{h,t} S_t \varepsilon_{j,t}, \end{cases} \tag{2}$$

where $\delta_{j,t}$ represents the selection vector with one on the $j-th$ position and zero otherwise, F_{t-1} is the information set until $t-1$, $\Psi^g_{j,t}(h)$ represents the GIRFs of variable j, and h represents the forecast horizon. Afterward, we can compute the GFEVD that is interpreted as the variance share one variable has on other variables j. The h-step ahead GFEVD $\widetilde{\varphi}^g_{ij,t}(h)$ can be calculated as follows:

$$\begin{cases} \widetilde{\varphi}^g_{ij,t}(h) = \dfrac{\sum_{t=1}^{h-1}\Psi^{2,g}_{ij,t}(h)}{\sum_{j=1}^{N}\sum_{t=1}^{h-1}\Psi^{2,g}_{ij,t}(h)}, \\ \sum_{j=1}^{N}\widetilde{\varphi}^g_{ij,t}(h) = 1, \\ \sum_{i,j=1}^{N}\widetilde{\varphi}^g_{ij,t}(h) = N. \end{cases} \tag{3}$$

Using the GFEVD, the total connectedness index can be obtained:

$$C^g_t(h) = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\varphi}^g_{ij,t}(h)}{\sum_{i,j=1}^{N}\widetilde{\varphi}^g_{ij,t}(h)} * 100. \tag{4}$$

First, we focus on the spillovers of variable i to all others j, representing the total directional spillovers to others:

$$C^g_{i\% \longrightarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\varphi}^g_{ji,t}(h)}{\sum_{j=1}^{N}\widetilde{\varphi}^g_{ji,t}(h)} * 100. \tag{5}$$

Second, we compute the spillovers of all variables j to variable i, representing the total directional spillovers from others:

$$C^g_{i\% \longleftarrow j,t}(h) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\varphi}^g_{ij,t}(h)}{\sum_{i=1}^{N}\widetilde{\varphi}^g_{ij,t}(h)} * 100. \tag{6}$$

Third, we subtract the total directional spillovers to others and total directional spillovers from others to get the net total directional spillovers:

$$C^g_{i,t} = C^g_{i\% \longrightarrow j,t}(h) - C^g_{i\% \longleftarrow j,t}(h). \tag{7}$$

If $C^g_{i,t} > 0$, it means that variable i influences the network more than being influenced by it. By contrast, if $C^g_{i,t} < 0$, it means that variable i is driven by the network.

3.2. BK Frequency Connectedness Approach. To examine the volatility spillovers among the major global financial markets in the frequency domain (long-, medium-, or short-term), we adopt the spectral representation of the variance

decomposition method based on frequency responses to shocks following Baruník and Křehlik [50].

The scaled generalized FEVD on a frequency band $d = (a, b)$: $a, b \in (-\pi, \pi)$, and $a < b$ can be defined as follows:

$$\begin{cases} \left(\widetilde{\theta}_d\right)_{j,k} = \left(\theta_d\right)_{j,k} / \sum_k \left(\theta_\infty\right)_{j,k}, \\ \left(\theta_d\right)_{j,k} = \dfrac{1}{2\pi} \int_d \Gamma_j(\omega) \left(f(\omega)\right)_{j,k} d\omega, \\ \left(\theta_\infty\right)_{j,k} = \sum_{d_s} \left(\theta_{d_s}\right)_{j,k}, \end{cases} \tag{8}$$

where $(\theta_d)_{j,k}$ denotes generalized variance decompositions on frequency band d, $\Gamma_j(\omega)$ denotes frequency share of the variance of the $j-th$ variable, $(f(\omega))_{j,k}$ represents the portion of the spectrum of the $j-th$ variable at frequency ω due to shocks to the $k-th$ variable, and d_s denotes an interval on the real line from the set of intervals D.

The frequency connectedness on the frequency band d can be obtained by

$$C_d^F = 100 \times \left(\frac{\sum \widetilde{\theta}_d}{\sum \widetilde{\theta}_\infty} - \frac{Tr\left\{\widetilde{\theta}_d\right\}}{\sum \widetilde{\theta}_\infty} \right), \tag{9}$$

where $Tr(\cdot)$ is the trace operator. This frequency connectedness framework allows us to identify the short-, medium-, and long-term volatility spillovers among the major global financial markets when setting frequency band d to different intervals.

4. Empirical Results

4.1. Static Analysis of Volatility Spillovers among Major International Financial Markets

4.1.1. Static Analysis of Spillover Effects under Different Stages

(1) Static Volatility Spillovers in the Time Domain. In this section, we first test the time-frequency volatility spillovers among the major international financial markets from the static perspective. About the parameters in the TVP-VAR-based connectedness and BK model, we keep the same forecasting horizon of $h = 10$ as in Diebold and Yilmaz [47]. The specific test results are shown in Table 2. The directional spillover index contains two categories, in which "From" represents the extent to which a financial market is influenced by other markets, denoting the inward inhalation spillover effect, and "To" represents the extent to which a financial market influences other markets, denoting the outward export spillover effect. According to the static analysis of time-domain volatility spillover effects in Table 2, from the perspective of the main international financial market variables as a whole, the total spillover index (TCI) represents the spillover effect of all other variables on one variable before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict at 55.63, 58.23, and 69.70, respectively, indicating that in addition to the effects of the market variables themselves, the 55.63% of the risk in financial markets before the COVID-19 pandemic comes from the spillover effect of correlated volatility between markets, while it rises to 58.23% and 69.70% during the COVID-19 pandemic and during the Russia-Ukraine conflict, respectively, indicating that COVID-19 and the Russia-Ukraine conflict were able to increase the linkages between gold, oil, natural gas, and the stock markets of six countries by 4.47% (2.60/58.23) and 20.19% (14.07/69.70), respectively.

From the perspective of specific variables, before the outbreak of the COVID-19 pandemic, the European debt crisis became the main factor plaguing the world economic development as the haze of the US subprime mortgage crisis had not yet wholly dissipated, with the USA (87.11%) and the European triumvirate of France (105.82%), the UK (93.48%), and Germany (91.45%), being the larger spillover propagators, which indicates that economies such as Europe and the USA have a substantial global influence in terms of extreme event outbreaks and stock market volatility. Furthermore, with the outbreak of extreme events such as the COVID-19 pandemic and the Russia-Ukraine military conflict, in order to cope with the liquidity crisis and avoid the financial crisis, on 15 March 2020, the Federal Reserve announced zero interest rates and launched a quantitative easing program of $700 billion and other countermeasures; the value of the contribution of spillover from the United States weakened, while financial markets such as Japan and Germany were unable to gain an interest rate advantage and their spillover influence increased. Affected by the conflict between Russia and Ukraine, gold, oil, and natural gas markets have not only shifted more spillovers but also have significantly been influenced by other markets. Where "Net" represents the "To" of each financial market as the result of subtracting the "From" of each financial market, it can be found that the natural gas market has become the recipient of the net spillover effect of volatility more and more affected by the COVID-19 pandemic. In contrast, the conflict between Russia and Ukraine has become increasingly tense. The global risk aversion has pushed the gold price higher and remained high. The spillover effect of the gold market rises from 12.39% during the COVID-19 pandemic to 91.66% during the conflict between Russia and Ukraine outbreak, making the gold market change from a net recipient of spillover effects to a spreader. In general, the static analysis of the time-domain volatility spillover effect found a strong interaction between the major international financial markets, which triggered a specific spillover effect after the outbreak of extreme events, providing investors with various investment strategies and portfolio schemes to avoid unexpected events.

(2) Static Volatility Spillovers in the Frequency Domain. In this study, the overall volatility spillover effect is analyzed separately according to different frequency domains, dividing the frequency bands into low, medium, and high frequencies and decomposing them into short-term frequency domain (1–5 days), medium-term frequency domain (5–20 days), and long-term frequency domain (more than 20 days) correspondingly. First, we focus on the volatility spillover effect of international major financial markets in the short-term

Table 2: Static volatility spillovers in the time domain.

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	32.36	15.69	2.89	13.64	18.01	11.81	3.33	1.17	1.11	67.64
UK	15.08	29.85	0.59	18.75	20.87	12.24	0.95	0.34	1.34	70.15
JPN	16.55	10.86	35.26	8.68	11.86	6.86	4.76	1.56	3.62	64.74
GER	12.93	19.25	0.59	27.21	24.51	11.04	1.37	0.55	2.55	72.79
FRA	15.19	19.75	0.82	22.76	27.28	10.48	1.19	0.62	1.91	72.72
CHN	15.53	16.18	2.76	13.43	15.38	34.43	0.53	0.87	0.88	65.57
Gold	3.63	4.81	1.54	6.57	6.16	4.87	69.06	1.49	1.87	30.94
Oil	4.11	3.34	1.61	3.38	4.47	2.71	3.92	74.24	2.22	25.76
Gas	4.09	3.61	5.59	4.25	4.57	2.43	3.64	2.21	69.62	30.38
To	87.11	93.48	16.4	91.45	105.82	62.43	19.7	8.81	15.5	500.68
Net	19.46	23.33	−48.35	18.67	33.1	−3.14	−11.24	−16.95	−14.88	TCI = 55.63
Panel 1. (b) During the COVID-19 period										
USA	31.15	16	6.12	15.71	16.18	8.71	1	4.35	0.79	68.85
UK	13.42	24.95	5.8	19.85	21.05	7.47	1.39	4.9	1.18	75.05
JPN	13.55	13.3	28.32	15.29	14.77	7.06	2.75	3.63	1.33	71.68
GER	13.09	19.56	5.73	24.64	22.22	7.4	2.21	3.96	1.19	75.36
FRA	13.25	20.6	5.54	22.07	24.51	7.14	1.58	4.25	1.07	75.49
CHN	10.83	10.71	7.9	10.86	10.44	40.51	1.45	4.96	2.35	59.49
GOLD	2.72	4.04	3.28	6.42	5.11	2.03	73.67	1.55	1.18	26.33
Oil	7.48	9.44	4.61	7.78	8.54	6.3	1.08	53.38	1.39	46.62
Gas	2.74	4.09	3.26	3.84	3.56	4.63	0.93	2.18	74.78	25.22
To	77.07	97.75	42.24	101.79	101.86	50.74	12.39	29.77	10.48	524.09
Net	8.22	22.7	−29.44	26.43	26.38	−8.75	−13.94	−16.85	−14.74	TCI = 58.23
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	29.67	10.67	2.37	13.85	13.97	3.54	13.46	9.55	2.93	70.33
UK	11.5	20.33	7.56	17.86	18.45	3.46	10.71	6.61	3.53	79.67
JPN	12.8	10.59	22.71	12.16	11.88	7.83	7.47	6.53	8.03	77.29
GER	10.45	15.13	4.51	20.28	20.55	2.56	14.08	8.86	3.58	79.72
FRA	10.46	15.31	4.58	20.19	21.09	2.6	14.04	8.53	3.2	78.91
CHN	9.35	2.31	4.36	2.67	2.93	64.82	2.8	2.75	8.01	35.18
Gold	9.26	8.08	3.2	14.23	14.72	3	27.31	16.78	3.41	72.69
Oil	7.95	5.64	5.98	10.81	10.85	7.49	19.56	25.36	6.37	74.64
Gas	7.53	4.29	6.27	8.79	8.41	9.24	9.55	4.81	41.11	58.89
To	79.31	72.03	38.82	100.55	101.75	39.73	91.66	64.41	39.05	627.32
Net	8.98	−7.64	−38.47	20.83	22.85	4.55	18.97	−10.23	−19.84	TCI = 69.70

Note. (i) The TCIs (TCI = 55.63, 58.23, 69.70) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

frequency domain and measure the relevant static volatility index. The specific test results are shown in Table 3. From the overall level of volatility spillover effect in the short-term frequency domain, the total spillover index (TCI) is 41.78, 48.05, and 62.67 before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict, respectively, indicating that there is a certain upward fluctuation trend in the volatility spillover effects of extreme events on major international financial markets in the short-term frequency domain. In specific analysis, it seems that before the COVID-19 pandemic, the spillover propagation contribution levels of the UK (69.56%), Germany (70.03%), and France (80.26%) were higher. When the extreme events broke out, they all showed a fluctuating trend of lower contribution values in the short-term frequency domain. The gold market, oil market, and natural gas market quickly become risk propagators for other market affiliates in the short-term frequency domain after the outbreak of extreme events; especially after the outbreak of the Russia-Ukraine military conflict, the spillover index of the gold market increases from 10.13 to 52.66, a rise of 80.76%; and the spillover index of the oil market increases from 25.42 to 67.59, a rise of 62.39%. The premium index of the natural gas market rose from 8.54 to 45.32, a rise of 81.16%.

When examining the financial market volatility spillover effect from the frequency domain perspective, there is a certain degree of cross-sectional correlation between the segment domains of medium, high, and low frequencies. Thus, medium frequency is examined as a transitional frequency band. Table 4 shows the volatility spillover effect of international major financial markets in the medium-term frequency domain. According to the results of the relevant static spillover indices, it can be seen that: from the overall perspective of the volatility spillover effect in the medium-term frequency domain, the total spillover index (TCI) was 7.01, 7.93, and 12.56 before the COVID-19 pandemic, during the COVID-19 pandemic, and during the Russia-Ukraine conflict, respectively, indicating that as the outbreak of extreme events severity increases, the more pronounced the volatility spillover effect among major international financial markets. Among them, the USA, as the world's largest economy, had a positive net spillover index

Table 3: Static volatility spillovers in the frequency domain (short-term).

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	24.47	11.77	2.17	10.97	14.33	8.8	2.49	0.8	0.8	52.12
UK	10.76	22.46	0.39	14.11	15.56	8.53	0.79	0.22	0.97	51.34
JPN	14.08	9.34	30.5	7.66	10.74	4.85	3.71	1.22	3.41	55.01
GER	8.83	13.67	0.4	20.56	18.09	7.42	1.17	0.39	2.03	52
FRA	11.26	14.98	0.67	18.13	21.56	7.62	1	0.45	1.53	55.64
CHN	10.34	10.7	1.97	9.02	10.24	24.1	0.42	0.61	0.52	43.81
Gold	2.83	3.71	1.25	5.07	4.78	3.84	60.18	1.23	1.59	24.31
Oil	3.28	2.66	1.06	2.23	3.31	2.03	3.33	66.33	1.7	19.6
Gas	2.92	2.76	4.29	2.83	3.2	1.68	2.75	1.79	59.52	22.22
To	64.32	69.56	12.2	70.03	80.26	44.77	15.65	6.72	12.54	376.05
Net	12.2	18.22	−42.81	18.03	24.62	0.96	−8.66	−12.88	−9.68	TCI = 41.78
Panel 1. (b) During the COVID-19 period										
USA	27.32	13.89	5.49	13.53	13.89	7.56	0.84	4.1	0.73	60.02
UK	11.25	20.75	4.75	16.38	17.31	6.12	1.14	4.16	0.94	62.04
JPN	10.46	10.19	21.96	11.62	11.16	5.42	2.11	2.67	0.95	54.57
GER	10.95	16.25	4.73	20.33	18.26	6.08	1.83	3.36	0.97	62.42
FRA	11.03	17.09	4.54	18.22	20.16	5.85	1.35	3.61	0.85	62.53
CHN	8.98	9.01	6.6	8.95	8.58	33.04	1.17	4.35	1.96	49.6
Gold	2.2	3.15	2.61	4.97	3.91	1.57	59.42	1.16	0.92	20.49
Oil	5.89	7.72	3.94	6.19	6.82	5.25	0.89	46.21	1.22	37.92
Gas	2.54	3.75	3.01	3.47	3.19	4.03	0.82	2.01	63.58	22.82
To	63.3	81.05	35.67	83.32	83.11	41.88	10.13	25.42	8.54	432.43
Net	3.27	19	−18.9	20.9	20.58	−7.72	−10.36	−12.5	−14.28	TCI = 48.05
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	16.09	5	11.63	3.84	4.98	15.9	3.47	6.38	4.27	55.47
UK	7.1	6.68	8.8	6.08	6.52	11.65	4.7	5.42	6.13	56.4
JPN	10.54	4.75	13.73	5.7	6.6	14.46	5.86	9.55	4.27	61.73
GER	5.37	6.39	12.33	12.25	10.58	7.3	8.27	6.73	5.81	62.78
FRA	5.64	6.36	11.69	11.56	11	8.73	8.04	7.05	4.89	63.96
CHN	13.06	5.86	8.41	4.02	5.47	24.56	4.16	9.94	4.97	55.89
Gold	7.4	3.87	11.95	7.86	7.38	7.47	14.97	13.8	7.32	67.04
Oil	8.3	3.27	9.25	6.41	6.22	7.94	11.98	22.12	7.65	61.04
Gas	12.7	4.74	20.72	5.1	6.82	14.73	6.18	8.73	13.72	79.73
To	70.11	40.25	94.79	50.57	54.58	88.18	52.66	67.59	45.32	564.04
Net	14.64	−16.16	33.06	−12.21	−9.38	32.29	−14.39	6.56	−34.41	TCI = 62.67

Note. (i) The TCIs (TCI = 41.78, 48.05, 62.67) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

Table 4: Static volatility spillovers in the frequency domain (medium-term).

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	2.48	1.22	0.6	1.36	1.4	0.72	0.13	0.39	0.11	5.94
UK	1.65	2.65	0.72	2.22	2.4	0.81	0.19	0.6	0.19	8.78
JPN	2.19	2.25	3.55	2.63	2.57	1.11	0.43	0.6	0.22	12.01
GER	1.61	2.12	0.67	2.75	2.54	0.82	0.29	0.5	0.17	8.72
FRA	1.63	2.24	0.68	2.47	2.8	0.79	0.17	0.53	0.18	8.7
CHN	1.19	1.02	0.84	1.34	1.22	4.82	0.26	0.56	0.32	6.75
Gold	0.36	0.68	0.46	1.11	0.92	0.32	9.1	0.24	0.17	4.25
Oil	1.01	1.35	0.68	1.23	1.36	0.81	0.13	3.75	0.23	6.8
Gas	0.08	0.1	0.15	0.14	0.11	0.34	0.09	0.1	7.99	1.12
To	9.71	10.99	4.81	12.51	12.51	5.72	1.7	3.52	1.6	63.07
Net	3.78	2.21	−7.2	3.78	3.81	−1.03	−2.55	−3.28	0.47	TCI = 7.01

Table 4: Continued.

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (b) During the COVID-19 period										
USA	4.15	2.69	0.13	2.03	2.73	2.24	0.08	0.08	0.21	10.18
UK	2.72	4.44	0.06	2.52	2.97	2.33	0.03	0.04	0.19	10.87
JPN	0.98	1.22	2.2	1	0.94	1.85	0.02	0.06	0.13	6.21
GER	2.48	3.39	0.08	3.88	3.81	2.31	0.03	0.05	0.24	12.39
FRA	2.41	2.98	0.05	2.75	3.48	1.93	0.03	0.05	0.24	10.44
CHN	3.27	3.43	0.26	2.52	2.97	6.06	0.06	0.09	0.11	12.72
Gold	0.47	0.71	0.08	1.05	0.83	0.7	5.23	0.06	0.22	4.12
Oil	0.57	0.33	0.15	0.27	0.36	0.14	0.23	5.12	0.2	2.24
Gas	0.24	0.3	0.18	0.43	0.33	0.36	0.05	0.27	7.53	2.16
To	13.15	15.05	0.99	12.57	14.94	11.85	0.53	0.71	1.55	71.33
Net	2.97	4.18	−5.22	0.17	4.5	−0.88	−3.59	−1.53	−0.61	TCI = 7.93
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	2.67	3.51	2.66	3.2	1.68	1.49	0.77	0.56	1.06	14.93
UK	2.03	5.2	2.9	4.76	2.78	1.45	1.28	0.26	2.45	17.91
JPN	1.74	3.13	2.83	3.12	1.61	1.1	0.74	0.82	0.93	13.19
GER	1.42	3.51	3.17	4.53	2.31	1.39	1.25	0.32	1.42	14.79
FRA	1.5	3.42	3.04	4.08	2.2	1.23	1.08	0.31	1.43	16.08
CHN	2.13	1.99	2.24	1.6	0.97	3.48	0.52	0.5	0.56	10.51
Gold	0.64	1.89	1.74	3.54	1.74	1.3	2.21	0.67	1.09	12.61
Oil	0.83	1.22	1.32	2.43	1.31	1.82	1.74	2.05	0.58	11.25
Gas	0.12	0.38	0.17	0.38	0.24	0.09	0.23	0.14	0.62	1.75
To	10.41	19.06	17.23	23.11	12.64	9.86	7.6	3.59	9.5	113.01
Net	−4.52	1.15	4.03	8.32	−3.44	−0.64	−5	−7.66	7.76	TCI = 12.56

Note. (i) The TCIs (TCI = 7.01, 7.93, 12.56) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

before and during the COVID-19 pandemic, while when the Russia-Ukraine military conflict breaks out, the net value was −4.52, and the US financial market switches from being the transmitter of spillover effects to being the receiver of risk impacts, probably because the country's active response policy attenuates the degree of risk spillover. From the medium-frequency volatility spillover effect, it can be seen that with the outbreak of extreme events, both the spillover index and spillover of the gold, oil, and natural gas markets gradually show an increase, indicating that the three markets play an essential role in the overall international market risk contagion when faced with extreme events.

Table 5 shows the measurement results of the volatility spillover effect of major international financial markets in the long-term frequency domain. From the overall view of the volatility spillover effect in the long-term frequency domain, the total spillover index (TCI) is 3.54, 5.39, and 6.25 before the occurrence of COVID-19, during the epidemic, and during the outbreak of the Russia-Ukraine conflict, respectively, indicating that the degree of extreme events is positively correlated with the volatility spillover effect between financial markets. From the net spillover index, it seems that the net values of major international financial markets show differential changes. The results show that few markets can affect only other markets or receive only other markets at the risk of extreme events, indicating that most markets are switching roles between transmitters and receivers. It is difficult to be alone in the impact of extreme events, as markets are interconnected as a whole.

Overall, when extreme events break out, comparing the period before the COVID-19 pandemic and the period of double overlap between the epidemic and the outbreak of the Russia-Ukraine military conflict, the short-, medium-, and long-term total spillover indices of the frequency spillover effect increased by 33.33%, 44.19%, and 43.36%, respectively, which indicates that the change in the total impact on the original time series affected by extreme events is to some extent dominated by long-term spillover factors, which suggests that the variation of the total effect in the original time series affected by extreme events plays a volatile role in all frequency domains. From the directional spillover index, it seems that the financial markets of the USA, UK, Germany, and France have higher volatility spillovers in different frequency bands. The reasons for this are that the strong economic power and sound financial policy regimes in Europe and the USA have a profound impact on international financial markets. However, in the short term, it appears that the US market is a volatility transmitter with a positive net volatility spillover effect, while with the broadening of the event scale, the USA gradually begins to become a receiver of volatility under the influence of extreme events. In the long run, the USA maintains better risk-resilient stability under the double blow of the COVID-19 pandemic and the Russian-Ukrainian military conflict with a net value of 2.86. In the time-series volatility spillover effect test, the Japanese market shows a significant volatility net receiver characteristic. From the perspective of the frequency domain, it is found that in the short term, under the double blow of the COVID-19 pandemic and the Russian-Ukrainian military conflict, Japan's net volatility spillover index turns positive. It shows that the Japanese market will change from a receiver of volatility risk to a risk spreader in a sufficiently long period. The spillover effects of the Japanese market will remain relatively stable during the outbreak of extreme events, similar to the double superposition of extreme events such as the COVID-19 pandemic and the conflict between Russia and Ukraine in the

Table 5: Static volatility spillovers in the frequency domain (long-term).

	USA	UK	JPN	GER	FRA	CHN	Gold	Oil	Gas	From
Panel 1. (a) Pre-COVID-19 period										
USA	1.23	0.61	0.3	0.69	0.73	0.36	0.08	0.19	0.05	3.01
UK	0.82	1.33	0.36	1.13	1.23	0.41	0.09	0.3	0.09	4.44
JPN	1.11	1.15	1.79	1.35	1.34	0.56	0.21	0.3	0.11	6.13
GER	0.8	1.06	0.34	1.39	1.3	0.41	0.15	0.25	0.08	4.39
FRA	0.82	1.13	0.34	1.25	1.44	0.4	0.09	0.26	0.09	4.37
CHN	0.6	0.5	0.42	0.67	0.62	2.43	0.14	0.27	0.16	3.37
Gold	0.18	0.34	0.23	0.57	0.48	0.16	4.57	0.12	0.09	2.17
Oil	0.51	0.68	0.34	0.64	0.72	0.41	0.07	1.85	0.11	3.48
Gas	0.03	0.04	0.06	0.07	0.07	0.16	0.04	0.04	3.97	0.52
To	4.86	5.51	2.39	6.38	6.49	2.87	0.87	1.72	0.79	31.87
Net	1.85	1.06	−3.74	1.99	2.12	−0.5	−1.3	−1.75	0.27	TCI = 3.54
Panel 1. (b) During the COVID-19 period										
USA	1.36	2.21	2.76	1.11	1.22	0.2	0.3	0.11	1.57	9.48
UK	1.04	3.27	2.91	1.53	1.9	0.31	0.42	0.18	2.24	10.54
JPN	0.74	1.58	2.61	0.92	0.98	0.16	0.26	0.19	1.09	5.92
GER	0.29	1.14	1.42	0.95	0.87	0.25	0.1	0.08	0.55	4.69
FRA	0.42	1.35	1.74	0.95	1	0.23	0.12	0.06	0.89	5.76
CHN	1.12	1.26	0.57	0.37	0.58	0.58	0.17	0.09	0.82	4.99
Gold	0.07	0.23	0.23	0.64	0.4	0.28	0.64	0.51	0.18	2.53
Oil	0.29	0.07	0.11	0.12	0.06	0.25	0.82	1.19	0.63	2.36
Gas	0.18	0.36	0.76	0.07	0.22	0.12	0.46	0.1	1.9	2.28
To	4.15	8.19	10.5	5.73	6.23	1.8	2.65	1.32	7.97	48.55
Net	−5.33	−2.35	4.59	1.03	0.47	−3.19	0.12	−1.04	5.69	TCI = 5.39
Panel 1. (c) During the Russia-Ukraine conflict period										
USA	2.59	1.69	0.15	1.27	1.69	1.4	0.05	0.08	0.16	6.49
UK	1.86	2.81	0.09	1.93	2.25	1.66	0.03	0.05	0.2	8.08
JPN	0.77	0.92	1.16	0.87	0.87	1.29	0.02	0.04	0.13	4.93
GER	1.69	2.2	0.1	2.62	2.65	1.6	0.02	0.06	0.22	8.54
FRA	1.58	1.86	0.04	1.73	2.17	1.27	0.02	0.04	0.17	6.71
CHN	2.21	2.31	0.25	2.06	2.38	3.72	0.05	0.1	0.22	9.57
Gold	0.34	0.49	0.15	0.98	0.83	0.52	2.58	0.08	0.19	3.57
Oil	0.49	0.38	0.33	0.96	0.94	0.39	0.14	2.7	0.39	4.03
Gas	0.4	0.46	0.34	1.19	1.08	0.58	0.04	0.24	4.23	4.35
To	9.35	10.32	1.45	11.01	12.69	8.72	0.37	0.68	1.68	56.26
Net	2.86	2.24	−3.47	2.47	5.98	−0.85	−3.2	−3.34	−2.67	TCI = 6.25

Note. (i) The TCIs (TCI = 3.54, 5.39, 6.25) are the average values of TCI. (ii) The connectedness results represent average connectedness estimates.

time series volatility spillover. Net shows a negative state of the net receiver. Convergence: the gold market, oil market, and natural gas market all show a certain degree of short-term volatility under the impact of extreme events, while the long-term level of the gold market, oil market, and natural gas market is more vulnerable to risk spillovers from other financial markets during extreme events, with net values of −3.2, −3.34, and −2.67, respectively, becoming net receivers of risk spillovers.

4.1.2. Network Visualization Analysis under Different Stages. Furthermore, this paper examines the volatility spillover effects of the financial markets of six countries, including Germany, the United States, the United Kingdom, Japan, France, and China, as well as gold, oil, and natural gas, under the influence of extreme events. Specifically, the net pairwise spillover networks of major international financial markets are constructed to outline the structural change in the risk contagion, paths, and roles among international financial markets during extreme global events. The nodes in the network represent each financial market, and the edges between the nodes denote the volatility spillovers between financial markets. The strength of the volatility spillover effect is indicated by the thickness of the line and the direction of the arrow to describe the direction of risk transmission between different markets, where the more significant the radius and darker the color of the node, the stronger the ability of the corresponding market to influence other financial markets, and the more risk is transmitted externally. It can be seen from Figure 1 that in the time-domain spillover network, France with the largest size and the darker color of the node, followed by the United States, the United Kingdom, and Germany, and the degree of volatility spillover in the United States and the United Kingdom is also at a high level, indicating that the center of the volatility spillover network of major international financial markets is concentrated in Europe and the United States, the reason for which may be due to the geographical location, the degree of economic development, and the degree of perfection of financial policies. Asian financial markets such as Japan and China mainly acted as recipients

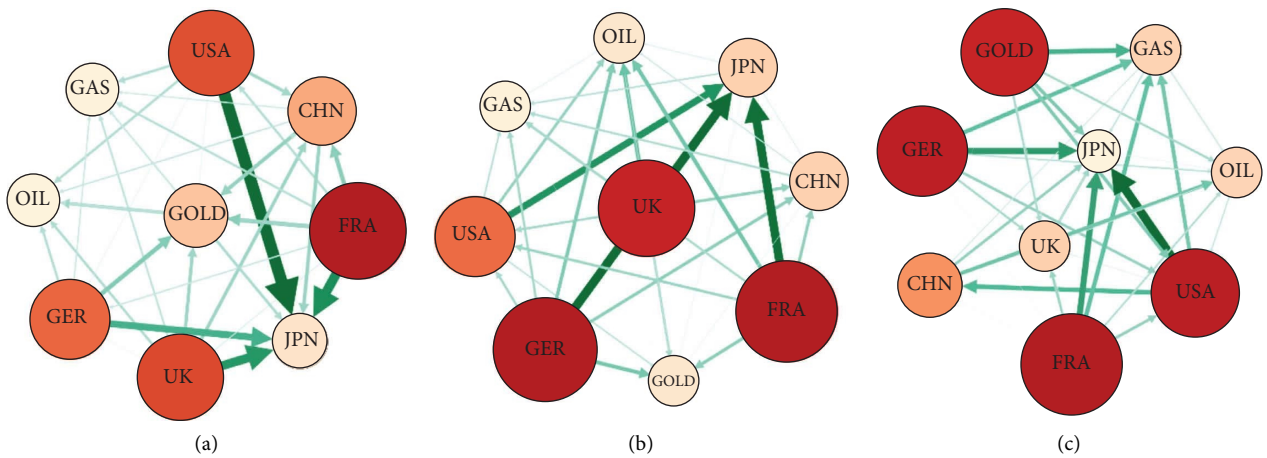


Figure 1: Time-domain volatility spillover network: (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the net pairwise directional volatility spillovers among the eight major international financial markets (based on the TVP-VAR-based connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.

of volatility risks before the COVID-19 pandemic, while during the COVID-19 pandemic, risks were dispersed to other markets such as gold, oil, natural gas, and so on. With the outbreak of the Russia-Ukraine military conflict, the volatility spillover index of the gold market rose. The reason for this may be that the subconscious reaction of the market triggers a strong risk aversion due to the Russian-Ukrainian conflict, and the gold market shows a sharp surge higher, becoming a transmitter from the receiver of the risk spillover, which in turn have an impact on the risk volatility of other markets.

The changes in spillover network structure under different frequency bands are shown in Figures 2–4. It seems that the USA, the UK, France, Germany, and other developed countries in Occident play a dominant role in most of the time and frequency domains. The risk spillover propagation from these countries' financial markets is stronger even under the extreme events of the COVID-19 pandemic and the outbreak of the Russian-Ukrainian military conflict. Only the intensity of risk spillovers from the UK market to other markets weakened after the outbreak of the Russian-Ukrainian military conflict, probably because the Russian-Ukrainian conflict has a more significant impact on the exchange rate of the euro economy, which also affects the currency movements of the British pound, thus making the UK a risk receiver. From the short-term frequency domain volatility spillover effect, the gold market quickly becomes a risk propagator in the short term under the double impact of the Russian-Ukrainian military conflict and the COVID-19 pandemic. The volatility spillover index is significantly higher, and with the window period extension, the gold market's risk spillover capacity is further enhanced. After the outbreak of the conflict, European and American countries quickly make sanctions against Russia, and thus, there was a need for the Russian energy market to turn to the East. In the long run, Japan and China appear to have significantly higher volatility spillover indices after being affected by the overlapping Russian-Ukrainian military conflict and the COVID-19 pandemic, with Japan showing the propagation of risk to the natural gas market and China spreading risk to the oil and natural gas markets.

4.2. Dynamic Analysis of Volatility Spillovers among Major International Financial Markets. The static analysis of time-frequency volatility spillover effects described in the previous section refers to the analysis results measured under different stages of extreme global events. However, only from the perspective of static spillover analysis to analyze the changes in volatility spillover characteristics among major international financial markets by dividing three stages of the extreme global events cannot comprehensively explain the whole sample period. Consequently, to capture the secular and cyclical movements in the volatility spillovers, this section further analyzes the dynamic characteristics of time-frequency volatility in major international financial markets. The dynamic fluctuations of the relevant volatility spillover indices (TCI and net) are plotted considering the time domain. Besides, the dynamic fluctuations in the frequency domain (short-, medium-, and long-term) are also presented separately.

4.2.1. Total Spillover Analysis. Figure 5 shows the dynamic distribution of the total spillover effects in major international financial markets in the time and frequency domains (short-, medium-, and long-term). In general, the total spillover index is in a state of flat volatility before the COVID-19 pandemic. When the COVID-19 pandemic broke out in January 2020, the total spillover index showed an upward trend, indicating that the epidemic risk significantly impacted the global economic and financial markets. Such risk had strong intermarket linkages and increased

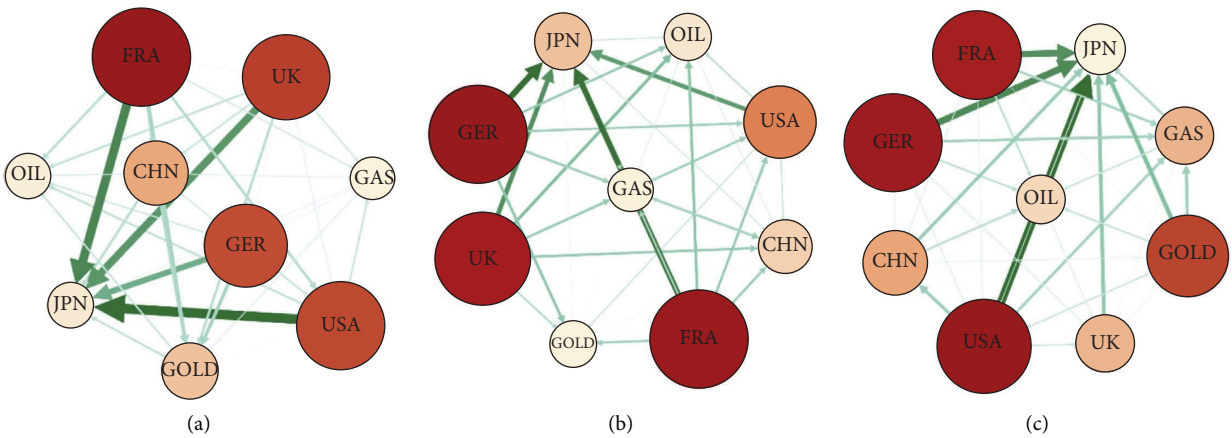


Figure 2: Frequency-domain volatility spillover network (short-term): (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the short-term net pairwise directional volatility spillovers among the eight major international financial markets (based on the TVP-VAR-based connectedness method and the BK frequency connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.

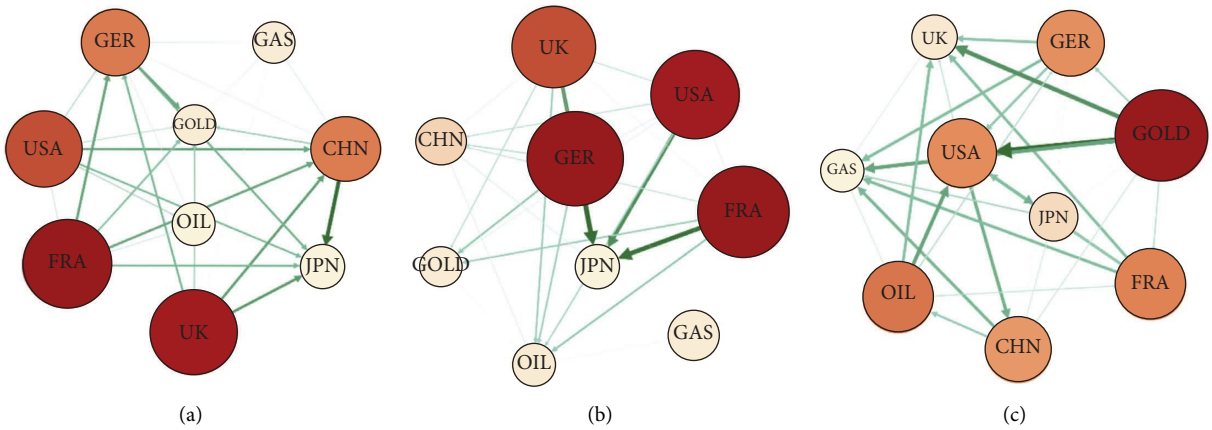


Figure 3: Frequency-domain volatility spillover network (medium-term): (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the medium-term net pairwise directional volatility spillovers among theeight major international financial markets (based on the TVP-VAR-based connectedness method and the BK frequency connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.

channels of risk spillover. The total spillover index reached its peak during the full period. After that, as countries become more experienced in facing the COVID-19 pandemic, the control strategy of the epidemic is gradually sound, and the relevant economic and regulatory policies operate effectively, the total spillover index shows a slow decline in the trend. The outbreak of the Russia-Ukraine conflict in February 2022 caused the total spillover index, which had fallen to its lowest point in terms of volatility, to rise again, and the war caused a global shortage of energy and rising costs, which affected the economic development of the major international financial markets. From the frequency domain distribution, it seems that all frequency domains show the same trend characteristics as the time-domain dynamic distribution at the critical points of the COVID-19 pandemic and the outbreak of the Russia-Ukraine conflict. The short-term level has the greatest volatility, and the long-term volatility is still pronounced, indicating that the impact of the COVID-19 pandemic and the outbreak of the Russia-Ukraine conflict lasted for a more extended period and that the shock was not the expected range of risk factors; thus, the total spillover index generates a larger volatility response to the shock of long-term structural factors.

4.2.2. Net Spillover Analysis. The net spillover index is the result calculated by subtracting the "To" of each financial market as the result of and the "From" of each financial

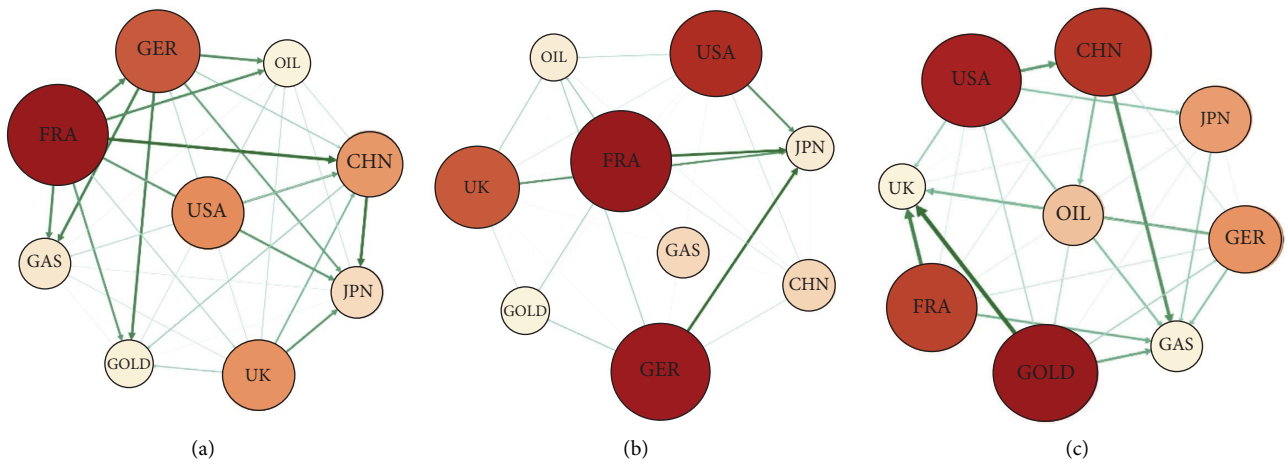
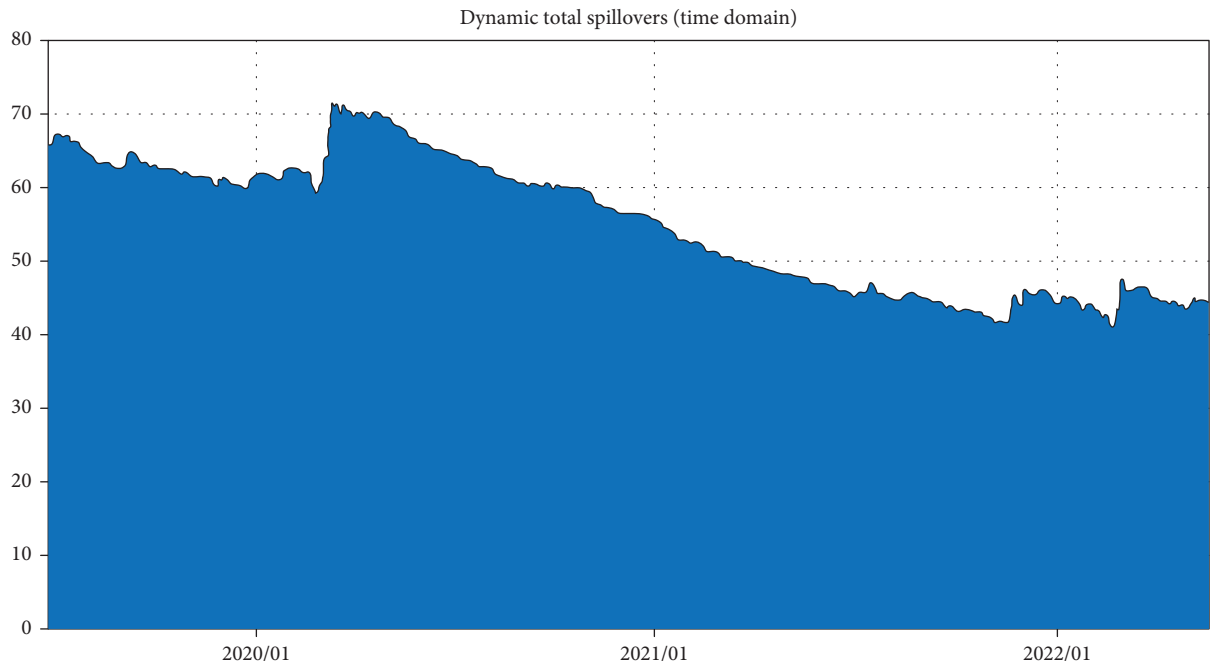
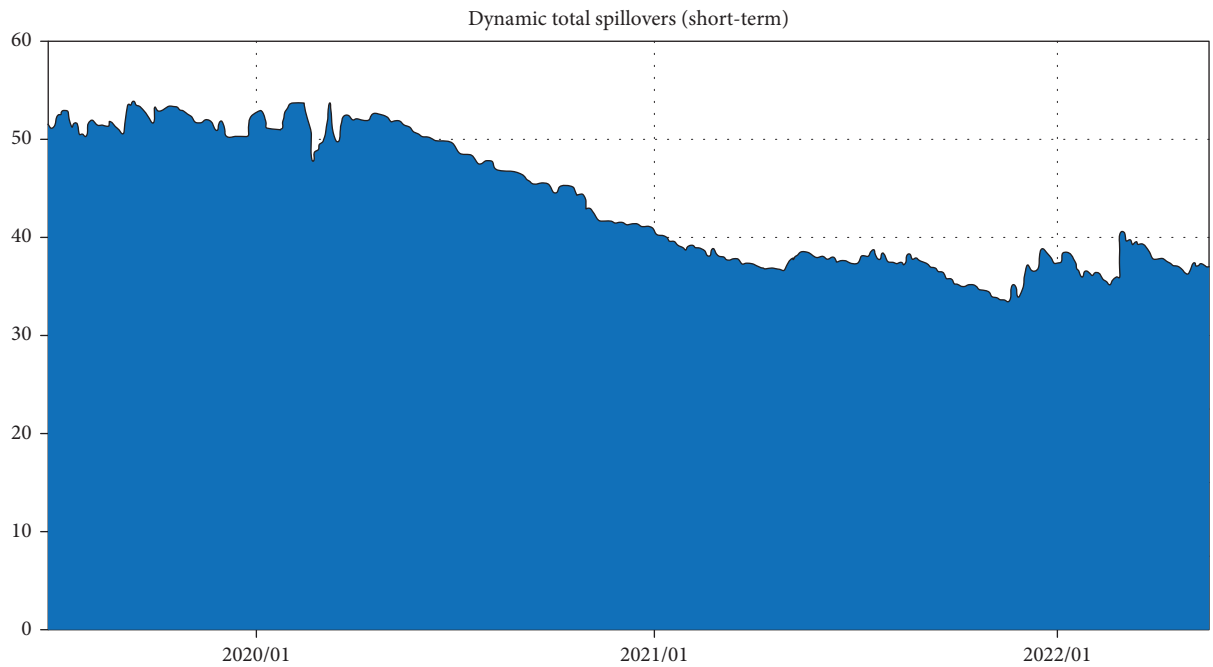


Figure 4: Frequency-domain volatility spillover network (long-term): (a) pre-COVID-19, (b) during COVID-19, and (c) during the Russia-Ukraine conflict. Notes: (i) These figures present the long-term net pairwise directional volatility spillovers among the eight major international financial markets (based on the TVP-VAR-based connectedness method and the BK frequency connectedness method) under different stages of the global extreme events. The node size reflects the overall magnitude of transmission/reception for each market. The edge size indicates the magnitude of the net pairwise volatility spillovers between two stock markets. Besides, the magnitude is also reflected through the color types of node/edge, dark (strong) versus light (weak) colors. (ii) The network topologies are estimated by the average spillovers.



(a)

Figure 5: Continued.



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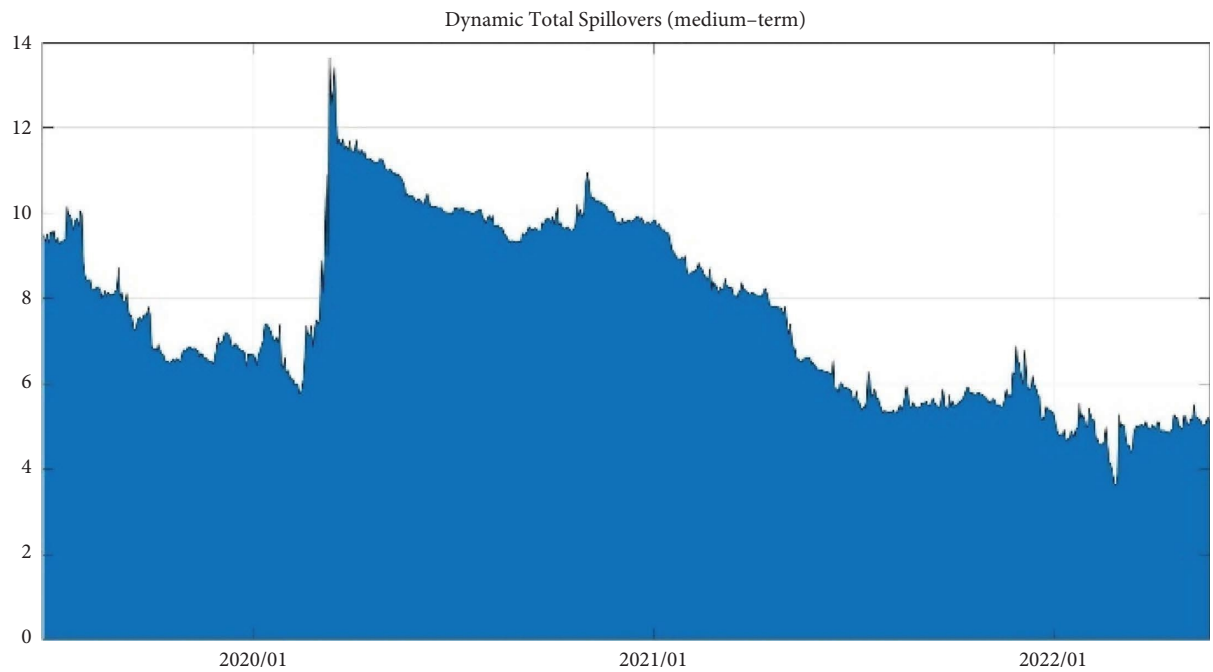

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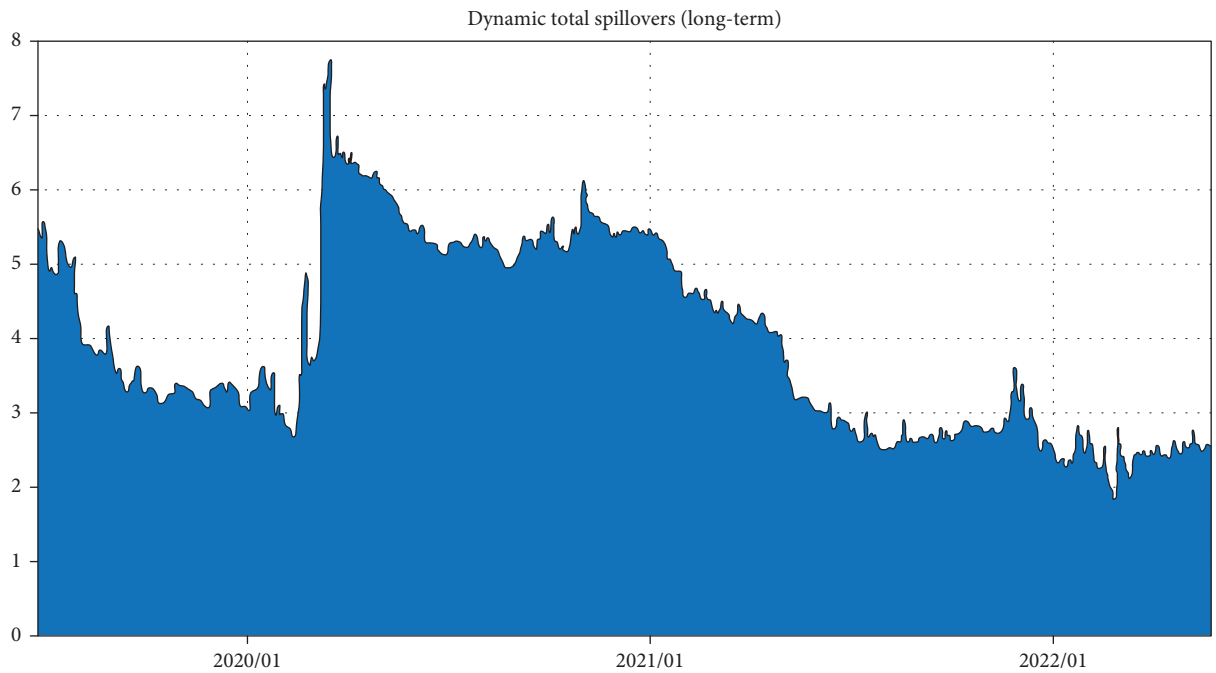
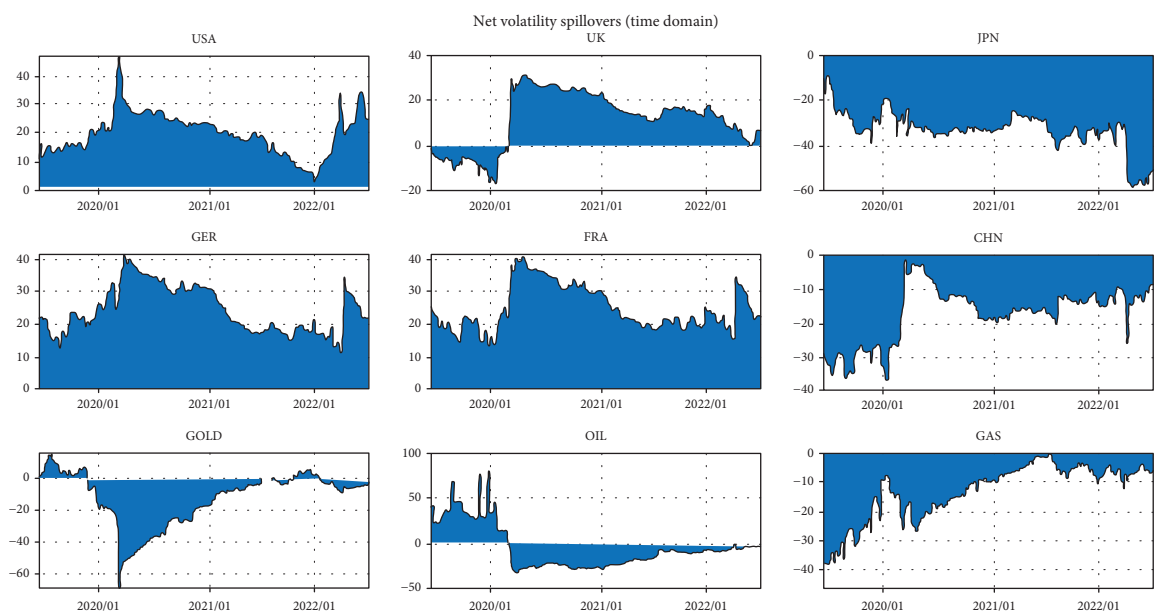


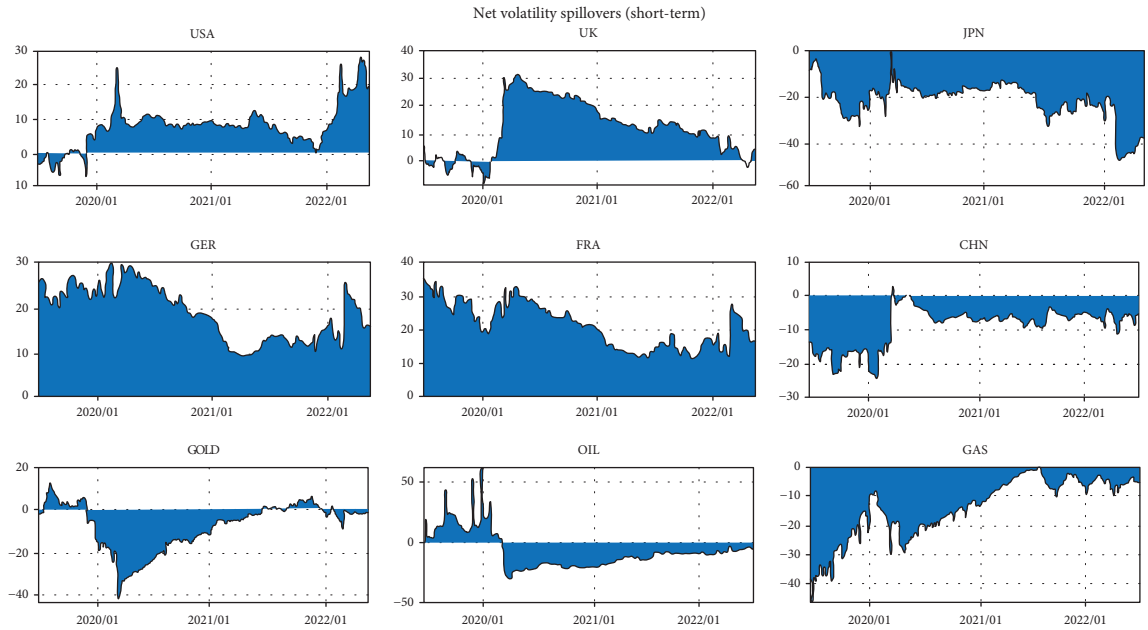
(d)

Figure 5: Total spillover index in time and frequency domains: (a) TCI (time-domain), (b) TCI (short-term), (c) TCI (medium-term), and (d) TCI (long-term).



(a)

Figure 6: Continued.



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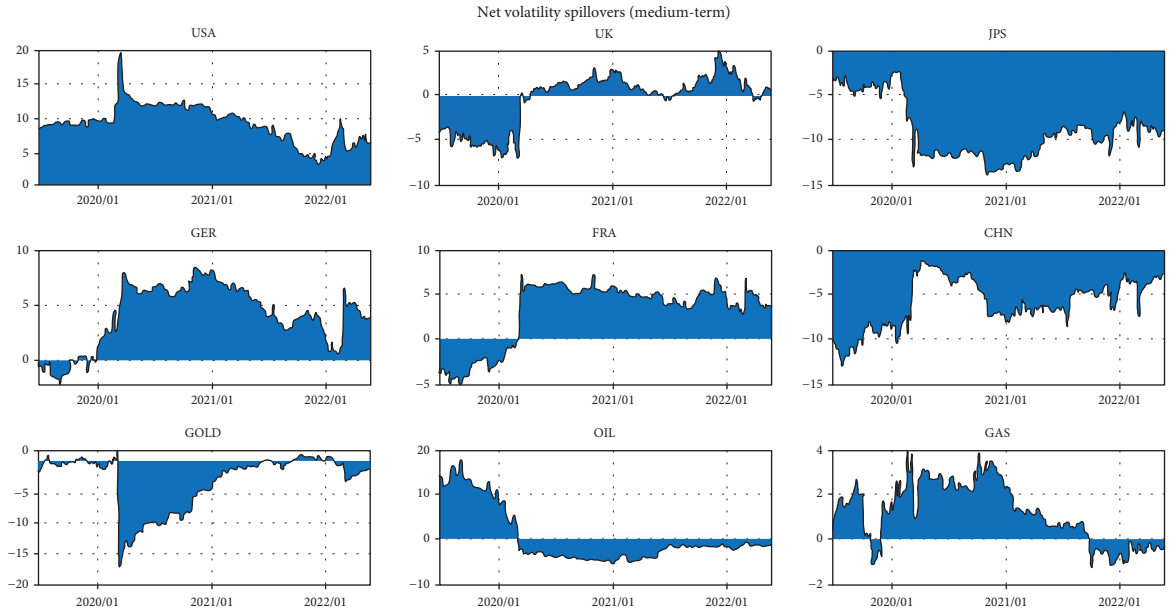

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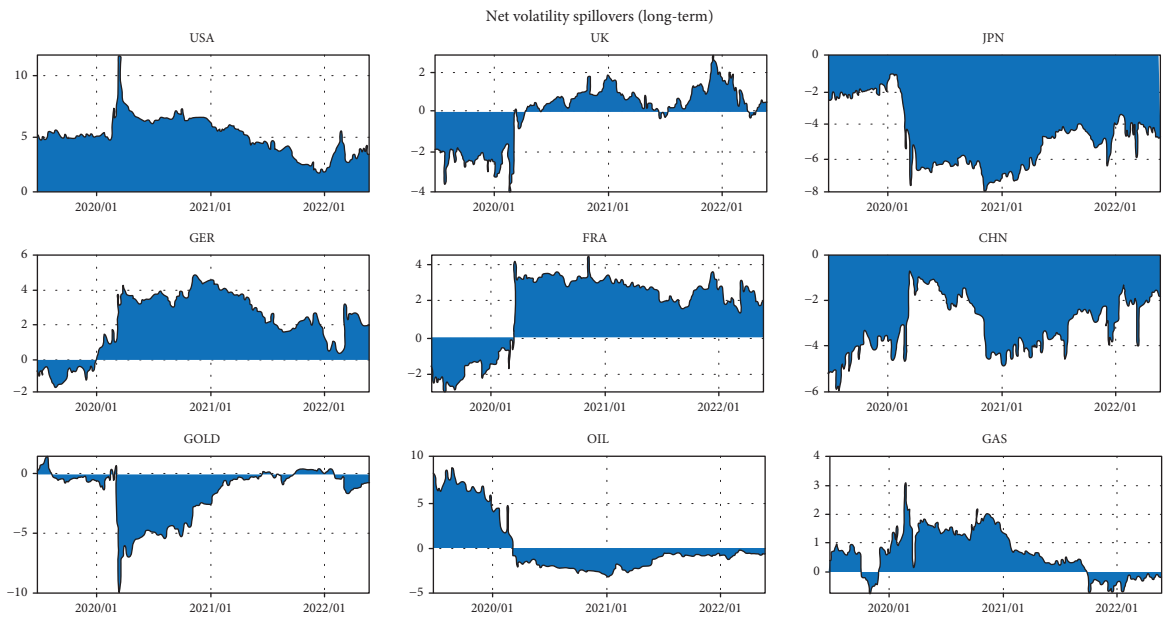

(d)

Figure 6: Net spillover index in time and frequency domains: (a) net (time-domain), (b) net (short-term), (c) net (medium-term), and (d) net (long-term).

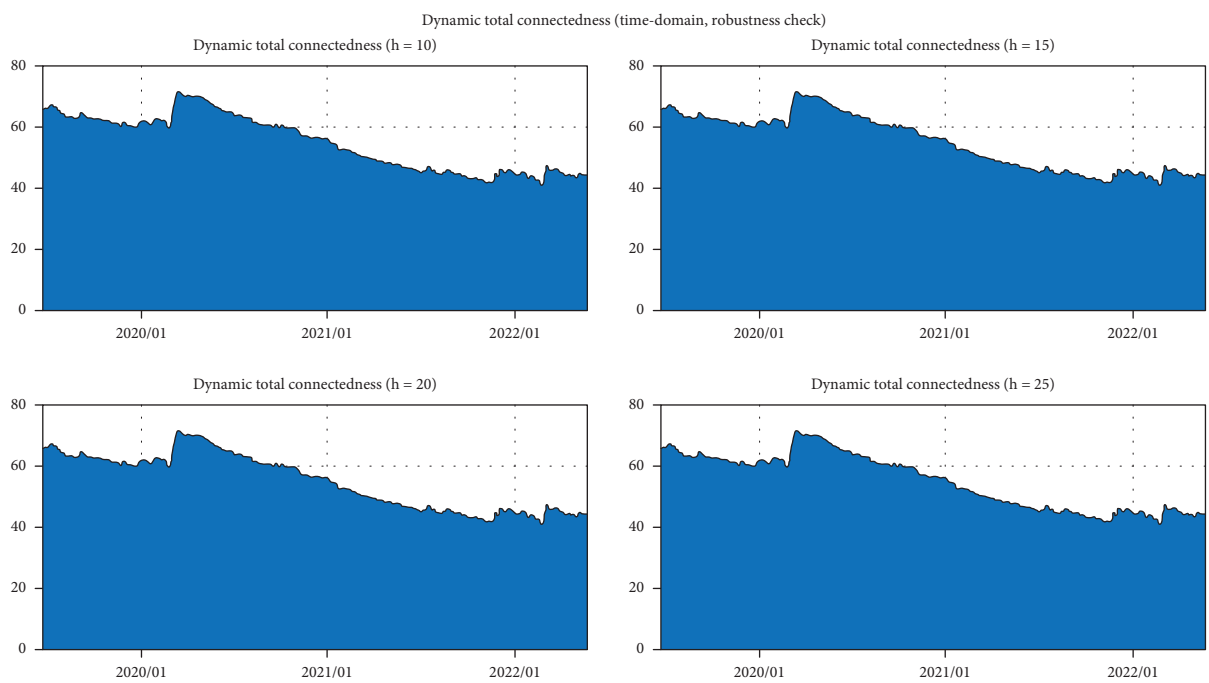

Figure 7: TCI in the time domain (robustness check).

market. According to the dynamic distribution of the net spillover index in Figure 6, it can be seen that six countries, including the United States, the United Kingdom, Japan, Germany, France, and China, as well as the financial markets for gold, oil, and natural gas, show significant changes in their characteristics in the face of the outbreak of extreme events. From a time-domain perspective, it is found that the values of the net spillover indices for the French and German markets are positive, the net spillover indices for the USA and the UK are positive over most of the period range, and the USA has a brief negative value in November 2021, probably related to the most significant increase in US inflation rate in 40 years of history during that period, indicating an increase in the natural gap in the US economy

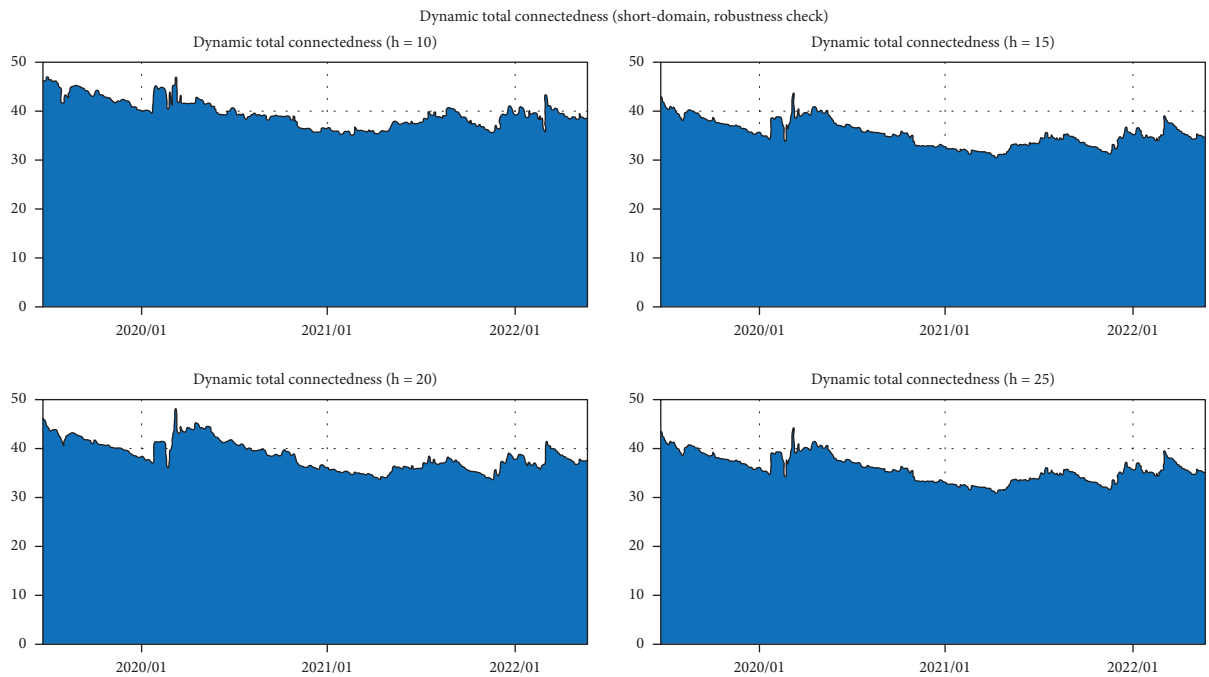

Figure 8: TCI in the short term (robustness check).

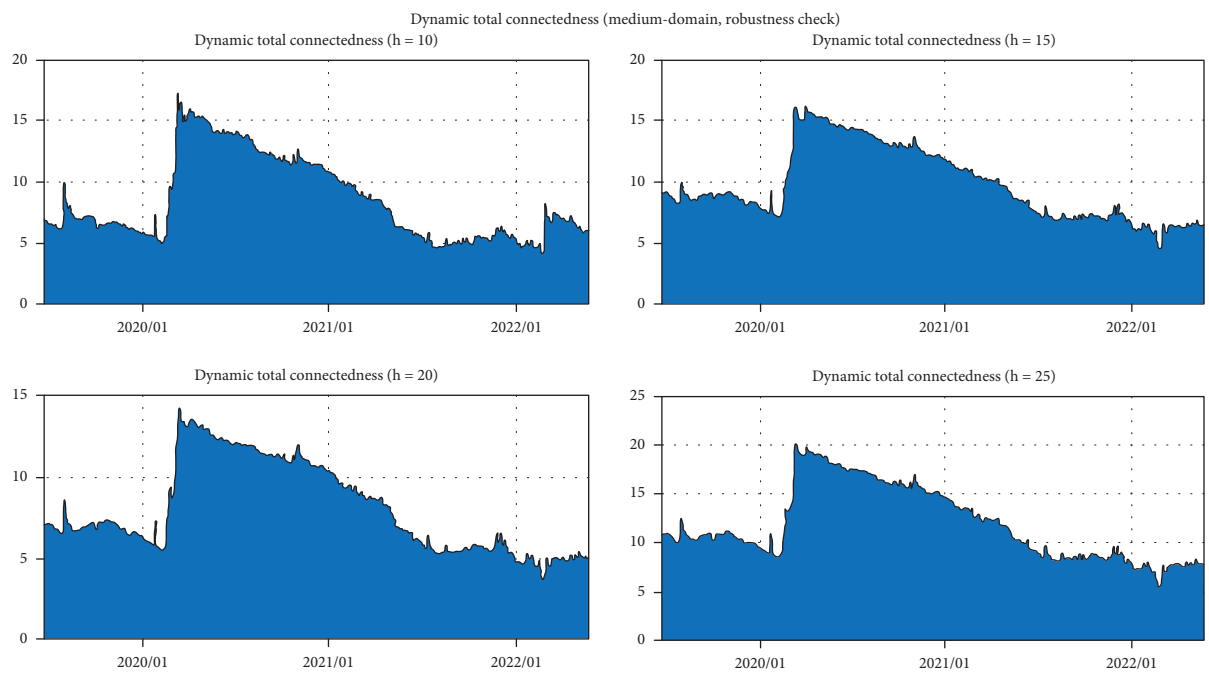

Figure 9: TCI in the medium term (robustness check).

during that period; the UK released a coexistence with the COVID-19 pandemic in early 2022 "lie flat" prevention policy in early 2022, which led to elevated UK input risk in other markets, thus briefly making the two markets net receivers of risk volatility in international markets. In contrast, Japan, China, gold, oil, and natural gas markets have almost always been in the role of risk receivers, among which the gold market, except for a profound volatility change at the time of the COVID-19 outbreak, gradually fluctuates smoothly in the middle range of risk receivers and risk transmitters with the occurrence of extreme events, reflecting the risk aversion property characteristics of the gold market. The COVID-19 pandemic and the epidemic response initiatives significantly worsen the US government deficit and debt problems, widen the income gap between residents and the rich-poor divide, reduce economic growth

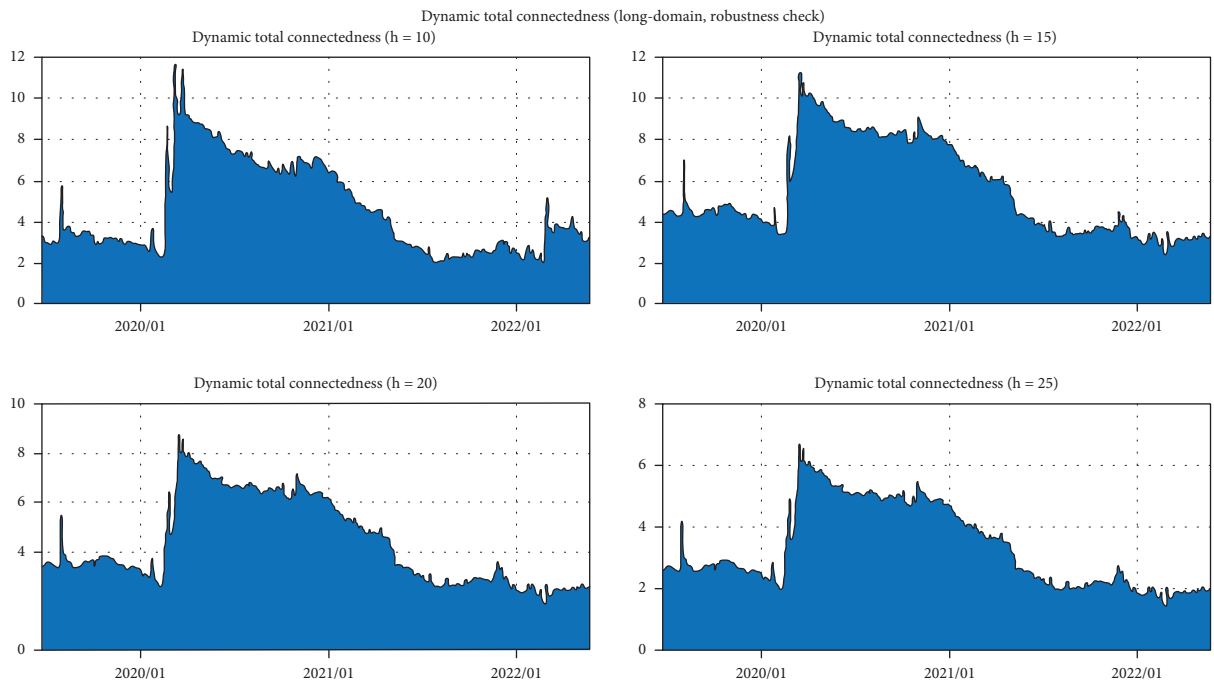

Figure 10: TCI in the long term (robustness check).

potential, and exacerbate the long-term unresolved structural problems of the US economy. Analyzed from the frequency domain perspective, the USA appears to have the highest increase in dynamic net spillover effect in the long term due to the impact of the COVID-19 pandemic, and other markets also reached a peak in the net spillover effect over a period of time range due to the influence of extreme events.

5. Robustness Check

In this section, we conduct robustness checks by setting different forecast horizons (h). Specifically, in the diagnostic tests, we choose $h = 15$, $h = 20$, and $h = 25$ to compare with the original TCI (other robustness check results are available if requested; dynamic total connectedness index) results by setting $h = 10$. The TCIs (dynamic total connectedness index) under the time domain and the frequency domain (short-, medium-, and long-term) are displayed in Figures 7–10. These figures show that the same results still stand under different forecast horizons, which supports the robustness of our results.

6. Conclusions

This paper examines the impact of multiple extreme events, such as the spread of the global COVID-19 pandemic and the outbreak of the Russia-Ukraine military conflict, on the financial markets of six countries, including the United States, the United Kingdom, Japan, Germany, France, and China, as well as gold, oil, and natural gas based on the time- and frequency-domain perspectives. First, to measure the impact of the extreme events the on the volatility spillovers among major international financial markets in the time-frequency domain, we combine the TVP-VAR-based connectedness method and BK frequency connectedness approach and focus on the total, directional, and net volatility spillovers. Second, the network visualization method is applied to outline the structural change in the risk contagion, paths, and roles among international financial markets during different periods of extreme global events.

First, we conduct the static spillover analysis. From a time-varying perspective, it appears that the outbreak of the COVID-19 pandemic and the Russia-Ukraine conflict led to higher volatility spillover risks during the outbreak; from the frequency domain, it seems that when extreme events broke out, the total spillovers among the international financial markets are affected significantly by the extreme events in each frequency domain.

Furthermore, net pairwise spillover networks are constructed to explore the impact of extreme events overlapping the COVID-19 pandemic and the Russia-Ukraine military conflict on the changes in the risk contagion paths and roles of the major international financial markets. From the time-domain net pairwise spillover networks, the French stock market with the highest level of volatility spillovers to other markets, followed by the United Kingdom, Germany, and the United States, indicate that the center of the volatility spillover network of major international financial markets is concentrated in Europe and the United States; in the frequency-domain network, the US market is the volatility transmitters in the short term, but as the window period lengthens, the level of spillover risk decreases under the impact of extreme events. The gold, oil, and natural gas markets all exhibit some degree of short-term volatility during extreme events. In contrast, at a long-term level, the gold, oil, and natural gas markets are more susceptible to risk

spillovers from other financial markets during extreme events.

Finally, the dynamic spillover analysis reveals that the total spillover index rises rapidly with the outbreak of the COVID-19 pandemic, and the Russia-Ukraine conflict puts the total spillover index, which has fallen to its lowest point with fluctuations, rising again. The frequency-domain distribution appears to show the same trend characteristics as the time-domain dynamic distribution at the critical points of the outbreak of the COVID-19 pandemic and the Russia-Ukraine conflict, whereas the short-term dimension has the greatest volatility spillovers, suggesting that volatility spillovers among international financial markets are driven mainly by the high-frequency component (short-term spillovers) during the full sample time. In terms of the net spillover index, France, Germany, the USA, and the UK are the main risk transmitters, while Japan, China, gold, oil, and natural gas markets have almost always been risk receivers.

Our results can provide some reference for researchers and investors worldwide to analyze market behavior and make investment decisions. On the one hand, it is a critical period for the outbreak of extreme events such as the COVID-19 pandemic and the Russia-Ukraine military conflict, enabling investors to avoid highly connected investment markets and categories, choose the portfolio solution with the lowest risk cost, and minimize the economic losses suffered due to unexpected events; on the other hand, it can help financial regulators and policymakers to identify the risk transmission fully and connectedness between international financial markets and other markets after an extreme event; identify the risk transmission linkages, paths, and spillover scale; analyze the time-varying connectedness and frequency connectedness among major international financial markets; and propose strategic guidance recommendations that are most in line with the current policy and financial system.

Data Availability

All the data used in this study are obtained from the Wind Database.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

All authors have made equal contributions to the paper.

Acknowledgments

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Research Article

How Energy Sector Reacted to COVID-19 Pandemic? Empirical Evidence from an Emerging Market Economy

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The European Union is facing the highest natural gas prices in 15 years, owing largely to an upward trend in electricity prices, which is also on an uphill curve. However, the rise in electricity and natural gas prices is a widespread phenomenon that is being felt not only in Europe but also globally, as economic activity resumes and energy consumption returns to prepandemic levels. Consequently, this paper investigates how COVID-19 influenced the Romanian energy market. To accomplish our goal, we used daily data for variables and market indices that characterize COVID-19 and the energy market from July 1 to December 21, 2021. The results of the GARCH (1, 1) model estimation show that the major performer in Romania's energy allocation and supply market had the highest conditional variance. In addition, the ARDL model was chosen because of the variable integration mix (order 0 and 1), as well as the VAR and the Granger causality framework. The empirical results of ARDL models provide the first conclusion of the analysis, indicating that the number of short-term connections was greater than long-term connections, which is also explained by the presence of short episodes of high volatility recorded in the investigated time interval. Another conclusion drawn from this study is that COVID-19 cases registered in Europe and around the world have made a significant contribution to explaining the evolution of the energy market, owing to the large number of cases registered in these regions and the level of contagion transmitted from these markets to the energy market. Furthermore, based on the Granger causality test results, only one-way causal relationships were identified from the variables that capture the evolution of the COVID-9 pandemic to the yields of Romanian energy companies. The novelty of this article is the examination of the impact of COVID-19 on the energy market throughout the fourth wave of coronavirus using the GARCH framework, the ARDL model, which allows for the capture of both short- and long-term reactions, the variance decomposition, and the Granger causality test. Because of the ongoing changes in the pandemic's evolution, additional research on this topic is undoubtedly on the horizon in the near future.

1. Introduction

Because of the lack of confidence, the pandemic might have an impact on international markets, causing asset prices to collapse across markets [1]. Since COVID-19 spreads quickly and has driven intensified economic insecurity [2], financial markets have plummeted and become extremely unpredictable, with significant drops in oil and metal prices [3, 4]. Szczygielski et al. [5] asserted that COVID-19 uncertainty has wreaked havoc on every national energy market. Naeem [6] supported that during times of crisis, market inefficiencies in the energy markets are more noticeable. As well, Zhang et al. [7] reinforced that the coronavirus calamity triggered considerable supply and demand shocks throughout the crude oil market. Although the oil supply and demand shocks related to COVID-19 are expected to be transitory, [8] their consequences on various sectors and nations are ongoing. In this regard, Wu and Ma [9] exhibited that COVID-19's energy price oscillations have a harmful effect on economic growth and inflation, with a larger impact on the latter variations. Following the outbreak of coronavirus, there have been several disruptions to economic activity leading to declining production and consumption. As well, individuals were inclined to remain at home when restriction measures were adopted, causing a substantial decline in trade and manufacturing activities,

which has an instant adverse effect on electricity usage [10]. Consequently, certain economic sectors were more affected, such as tourism, industry, and transport. According to Phillips [11], it is expected that the COVID-19 virus will grow endemic, but it may become less harmful over time. The return of global activity, as the restrictions imposed by the pandemic were lifted and the economies were completely reopened, led to a quick increase in demand for natural gas, both for electricity generation and for industrial purposes. In this regard, Yu et al. [12] claimed that throughout critical situations, natural resource commodities have shown to be extremely volatile. Also, the dramatic drop in crude oil prices has a substantial adverse effect on the low-carbon economy [13]. Hence, the carbon futures market was as well distorted. For instance, Dou et al. [14] emphasized that the carbon trading market has been substantially affected by the high-frequency price oscillations of carbon assets. Duan et al. [15] argued that when the economy is powerful and carbon prices are soaring, the effects of energy costs on carbon prices are less severe than when the market is fragile and carbon prices are the low point.

During the summer of 2021, this condition was amplified by the strong demand for electricity production, against the background of heat waves, while reducing production from competing sources (hydro and wind) and the appearance of supply constraints, caused by extreme weather events or prolonged maintenance work (given the postponement of some of the latter in the acute phases of the pandemic). According to Li et al. [10], an unexpected variation in energy demand can have a detrimental effect on both energy services and economic decisions because it provokes issues in energy infrastructure consistency and oscillations in energy distribution systems. Specifically, in Romania, the final energy consumption was 46125.7 million kWh from January to October 2021, up 5.3 percent over the same period in 2020, while public lighting climbed by 2.6 percent and private consumption increased by 7.4 percent [16]. Bahmanyar et al. [17] reported that weekday consumption was significantly reduced in states with severe constraints (Spain, Italy, Belgium, and the United Kingdom), and energy consumption patterns were comparable to prepandemic weekend profiles for the same period in 2019. Nevertheless, the decrease in electricity usage was lower in countries with less restrictive policies. By focusing on Canadian data, Khalil and Fatmi [18] reported that the regular average in-home duration of each occupation increased by about 80% throughout the disease outbreak, causing a 29% boost in energy utilization. Similarly, Surahman et al. [19] confirmed that throughout the coronavirus period, the average annual energy utilization in Indonesia's major cities is higher than prior to the pandemic. On the contrary, Kang et al. [20] proved in the case of South Korea that through the pandemic period, most amenities energy utilization has gradually diminished. In the same vein, Wang et al. [21] confirmed that COVID-19 has reduced China's electricity consumption by 29%.

This research explores how the COVID-19 pandemic influenced the Romanian energy market throughout the fourth wave of coronavirus. The motivation for exploring Romania is depicted by the fact that it ranked first among all European member nations and sixth internationally during the fourth COVID-19 wave. As well, according to European Centre for Disease Prevention and Control [22], in the penultimate week of December 2021, Romania has the second-lowest vaccination rate in the European Union (EU), with only 41.2 percent of its 19.3 million people fully vaccinated against COVID-19. Since 2019, Romania has switched from being an electricity exporter to a net importer, despite having historically had the third lowest rate of energy import dependency in the EU due to its natural gas and oil reserves and a large power generation sector. Also, coal, hydropower, fossil gas, nuclear energy, and wind power all contribute roughly equal amounts of capacity and power generation to Romania's electricity mix, which is one of the most balanced in the EU [23].

Our paper's specific goals are to investigate the reaction of the energy market during the pandemic period from July to December 2021. The first goal is to examine the volatility of selected variables that characterize the energy market, namely stock market indices corresponding to the energy sector (e.g., EEX-B, EEX-P, APX, and LNGI), the Romanian energy market specific index (e.g., BET-NG), as well as companies traded on the Bucharest Stock Exchange (BSE) (e.g., SNG, EL, TGN, and TEL). The GARCH model will be considered in this regard. The second goal is to investigate long-term and short-term relationships between energy market variables and the number of new COVID-19 cases in Europe and globally. The ARDL (autoregressive distributed lag) econometric model will enable us to examine such associations [24]. Third, we will approach variance decomposition using VAR (vector autoregressive models) models to further investigate the level of explanation of COVID-19 variables on the variation of selected energy market measures. Fourth, we will investigate the type of causality that has been established between the new number of COVID-19 cases and the energy market. In this vein, after all, data series have been converted to stationary series, the Granger causality test will be applied.

Crude oil prices shape macroeconomic dynamics by affecting monetary policy instruments, inflation, as well as other business activity, in addition to their impact on corporate earnings [25]. For the reason that oil price shifts have such a large impact on macroeconomic performance, exploring this effect and predicting how vulnerable economic development will be during crises is critical [12]. This research adds to the existing body of knowledge in a number of ways. First, to the best of our knowledge, the study provides the first empirical evidence for the case of Romania. Prior studies were focused on a diverse worldwide sample [4, 26], several European countries [17], China [9, 13, 21, 27–32], G7 nations [33], Indonesia [19], South Korea [20], United States [32, 34–36], Germany and United States [10], Canada [18], United Kingdom [37], United States and China [38], United States and Japan [39], China and Nigeria [40], Turkey [41], various countries with the leading energy sectors by market capitalization [5], emerging economies [2], or advanced and developing nations [42]. Hence, the evidence for emerging market economies is

limited. Secondly, the most recent COVID-19 wave is covered, namely the period from July 1 to December 21, 2021. Thirdly, different from prior papers that employed merely the worldwide pandemic cases [3, 24, 43, 44], our econometric investigation covers both new cases of COVID-19 pandemic globally and in Europe. As well, contrary to prior papers that used the price of WTI crude oil [1–4, 7, 8, 24–26, 29, 33, 35, 39, 43, 45–56], Brent crude oil [4, 7, 8, 15, 24, 26, 36, 37, 43, 44, 46, 47, 49, 51, 52, 54–56], Dubai crude oil [4, 8], NYMEX's oil [26, 55, 57], or carbon futures [14], the current study covers the daily returns of the Physical Electricity Index, Amsterdam Power Exchange Electricity Netherlands Average All Hours and, London Natural Gas Index United Kingdom Pence Per 100000 British Thermal Units. Not least, different from prior papers focused on time-frequency connectedness [32, 42, 55, 56, 58], our quantitative framework covers several techniques such as GARCH estimation, autoregressive distributed lag (ARDL) models, as well as vector autoregressive (VAR) models. Aside from empirical contributions, our findings have practical implications for policymakers throughout the unprecedented phase of insecurity triggered by the COVID-19 pandemic.

This paper is organized as follows. The second section examines the previous literature. The third section presents the research sample and the selected variables, along with the applied quantitative methods. The fourth section discusses the empirical results, and the final section concludes the article.

2. Background Literature

Many other regions of the world have experienced a dramatic increase in energy prices during the period under review. This may be due to the increase in global energy demand (especially natural gas), as the process of economic recovery has intensified since the peak of the COVID-19 pandemic. An elementary explanation, demonstrable in numbers, is that the demand for energy in 2021 has grown too fast compared to the increase in supply. However, the explanations for this deficit are numerous: in 2020, investment and maintenance works in electricity or natural gas capacities were stopped, especially LNG in the USA; industrial demand increased significantly in early 2021 after the 2020 lockdown periods; demand in Asia has recovered from other regions and attracted a large share of global liquefied gas supplies; the spring of 2021 was colder and more gas and electricity was consumed for heating; there have been gas production problems in the US due to Hurricane Ida, and so on.

It was expected that the economic activities of all households would be completely stopped throughout the world during the COVID-19 period. Most people were locked up in their homes and confined without work, which led to a loss of income. Additionally, living in homes during the pandemic has increased the electricity bill. Therefore, the situation of loss of income and increased electricity bills was a huge economic and financial burden for households [59]. Furthermore, concern for a worldwide recession has generated unavoidable systemic risks in the energy markets, exposing investors who own oil-derived securities to detrimental changes in crude prices [46]. The study by Zhang and Wang [57] demonstrated that the disease has increased long-term volatility for all future returns. Also, Shaikh [52] proved that through disease eruptions, the WTI crude oil market exhibited exceptional overreaction and dealt at an extremely volatile level. Dutta et al. [53] noticed that after the events related with COVID-19, there was a sizeable decline in worldwide crude oil prices, with the effect being highest when this novel coronavirus infection was announced a pandemic.

Crude oil is sometimes considered an economy's blood, and as a reason, oil price variations have a significant impact on many countries throughout the world [24]. For instance, Tong et al. [27] claimed that jumps in the oil market were the most strongly connected to the disease, notably through the peak and refall stages. The COVID-19 pandemic has put the energy markets under stress, but its most direct impact was on energy consumers through isolation measures that have deepened preexisting energy poverty problems, increased residential demand due to increased occupancy, and reduced the earnings of many families that have been economically affected by the crisis [60]. Narayan [61] noticed that the COVID-19 period is defined by one of the most severe drops in oil prices, with the price reaching a new low and the volatility rising by up to 900 percent.

The impact on the energy sector has led to an increased demand for residential energy as a result of reduced mobility and a change in the nature of work. Blockades around the world at the beginning of the pandemic have restricted movement and placed people at home, which in turn has reduced the demand for industrial and commercial energy, as well as waste generation [62].

The first strand of literature explored the impact of coronavirus diseases on energy stock returns. For example, Huang and Liu [30] found that after the pandemic period, the risk of Chinese energy companies' stock price fall down has considerably lessened. Further, the relationship between the COVID-19 pandemic, the oil yield, and the profitability of stocks in a unified framework was achieved using a TVP-VAR model by Liu et al. [35]. There was noticed a negative association between crude oil and stock yields during the sampling period. Contrary to many people's beliefs, the outbreak of the COVID-19 pandemic could have a significant positive impact on the crude oil market and the stock market. In this regard, Aloui et al. [63] argued that the S&P GS indexes of energy markets respond to the COVID-19 crisis in various ways throughout time due to fundamental and behavioral characteristics.

Pavlyshenko [64] studied different regression approaches to model the spread of COVID-19 and its impact on the stock market. The logistic curve model was used with Bayesian regression for predictive analysis of coronavirus spread. The impact of COVID-19 was examined using regressions compared to other effects of the crisis. Empirical results showed that different crises with various causes have a distinct impact on the same stocks.

In the same way, a statistical analysis of the effect of the COVID-19 pandemic on stock market risk was also conducted by Zhang et al. [65]. The virus has killed thousands of people and brought significant challenges to countries around the world. The results showed that the risks to the global financial market have increased substantially in response to the pandemic. For instance, Wang et al. [36] supported the transmission of risk among the coal and WTI crude oil markets. Individual reactions in the stock market are clearly related to the severity of the outbreak in each country. The high uncertainty of the pandemic and the associated economic losses have made markets extremely volatile and unpredictable. Political reactions are required to fight the virus and the level of stock markets. However, unconventional policy interventions, such as US quantitative easing (QE), create additional uncertainty and could cause long-term complications. Furthermore, countries do not work jointly to meet these challenges, as markets react differently to national policies and the overall development of the pandemic. Hence, this trend of fragmentation in the global community is more of a threat than a virus.

The new coronavirus has generated significant volatility in financial markets, including the commodity market. Argued by the fact that oil prices have fallen the most since 1991, the second strand of literature was oriented toward the volatility investigation of oil markets throughout the pandemic period. The time-varying total volatility spillovers across markets were noticed to have strengthened with the occurrence of COVID-19 and global crude oil price turbulence throughout the pandemic [31]. Ashok et al. [26] exhibited increased co-movements in energy markets appearing months prior to co-movements in equity markets. For instance, Akyildirim et al. [42] explored 29 developed and developing states and found that oil-exporting nations predominantly spread shocks, while oil-importing states mostly receive shocks. Si et al. [28] claimed that the COVID-19 shock is one of the main factors for the Chinese energy markets to become even more volatile. Likewise, Yousaf [47] supported that the volatility of the WTI oil market increases as the volatility of COVID-19 volatility rises. Also, Wang et al. [34] found that the price of oil in the United States has fallen along with the number of new instances that have been confirmed. Albulescu [66] studied how COVID-19 figures, in terms of daily announcements of new infections, have influenced international oil prices. The ARDL estimate showed a negative and significant impact on the coronavirus crisis but was relatively small compared to the effect of financial volatility and uncertainty in economic policy on oil prices. However, the influence of the pandemic on oil prices was indirect, and the volatility of mainly affected financial market. In addition, Albulescu [67] emphasized that the downward fluctuations of crude prices are driven by increased insecurity. The outcomes were also supported by Jeris and Nath [37], and Geyikçi [41]. Narayan [61] reinforced that the oil market has become unprofitable over the COVID-19 time frame using technical moving average trading techniques. Lin and Su [50] found that subsequent to the eruption of COVID-19, there is a dramatic rise in total connectedness in energy markets, but this shift merely persists about two months prior to returning to preinfection levels. Therefore, Iglesias and Rivera-Alonso [51] argued that volatility peaks occur throughout periods of supply/demand downturns or oil instabilities, whereas cycles with financial turmoil as the main trigger are associated with higher volatility persistence.

Other studies explored the impact of pandemic news on the energy sector. For instance, Albulescu [68] examined the impact of official COVID-19 announcements and related statistics on financial volatility, comparing the effect of data reported in China with those of COVID-19 records reported outside China. Empirical results exposed that only new cases reported outside China have a positive effect on the VIX index. Also, the death rate has a positive influence on the VIX index for all estimated models, but the effect was greater for the death rate outside China. In addition, the spread of the pandemic increased financial volatility. As such, the persistence of COVID-19 could generate a new episode of global financial stress. Amamou and Bargaoui [49] found that the release of a new disease outbreak wave lessens dependence on the oil market, which losses its attributes as a safe-haven market in favor of other markets such as gold or cryptocurrencies. Shaikh [54] exhibited that global crude oil is negatively associated with the news connected to the COVID-19 pandemic.

Further, Akhtaruzzaman et al. [69] investigated how financial contagion occurs through financial and nonfinancial firms between China and the G7 countries. Empirical results revealed that the dynamic conditional correlation (DCC) between the profitability of Chinese financial stocks and the financial and nonfinancial G7 increased significantly during the COVID-19 period. However, the magnitude of DCC growth has been greater for financial firms, implying that they exert a more critical role in transmitting the financial contagion than nonfinancial firms. The results showed that China and Japan appear to be net emitters of COVID-19 contagion. In addition, optimal hedging ratios increased substantially in most cases during the COVID-19 phase, leading to higher hedging costs during the crisis. The findings of Jiang and Chen [55] also indicate that overall connectedness has increased significantly since the COVID-19 outbreak, as compared to the preCOVID era. Jiang and Chen [58] confirmed that following the COVID-19 outbreak, overall connectivity has increased. Equally, Mensi et al. [38] exhibited that during the low-volatility period (high volatility regime), oil was a prominent recipient (contributor) of spillovers. Chen et al. [32] remarked that prior to the COVID-19 pandemic, the role of energy commodities as net receivers can be noticed in both the short and long terms, but following it, the net transmitter position can be seen in the long term.

Further, a review of earlier research exploring the influence of the COVID-19 pandemic on energy markets is provided in Table 1.

3. Research Methodology

3.1. Sample and Variables. The European Union, similar to various other regions of the world, is currently facing a sharp

Table 1: Summary of prior literature on the COVID-19–energy market nexus.

Author (s)	Period	Variables	Methodology	Outcomes
Ma et al. [29]	January 1, 2019–April 1, 2021	Oil prices and the GDP	Wavelet power spectrum, wavelet coherence, frequency domain causality test	The price of natural resource commodities has been observed to be more volatile throughout the COVID-19 timeframe
Yu et al. [12]	2007–2009, 2010–2018, 2019–2020	GDP and oil prices	Wavelet analysis	In the long-term, a jump in crude prices has effects on economic growth
Ali et al. [25]	March 2020–May 2020	Closing spot prices of WTI crude oil futures and stock indices of the United States, Canada, China, Russia, and Venezuela	Wavelet-based granger causality	Throughout times of stability, oil is vital for hedging, and during times of crisis, it serves as a safe-haven asset
Mensi et al. [70]	April 23, 2018–April 24, 2020	S&P500 index, brent oil, and gold futures	Bivariate FIAPARCH model	For all sub-periods, oil offers greater hedging efficiency than gold
Atri et al. [3]	January 23, 2020–June 23, 2020	WTI oil price, the worldwide confirmed new cases, and deaths	ARDL analysis	During the COVID-19 contagion, economic and financial instability has a detrimental effect on oil and gold values
Gharib et al. [71]	November 1, 2019–December 31, 2020	Daily west Texas light crude oil and north sea brent crude, diesel, and gasoline prices	Supremum augmented Dickey-Fuller, generalized supremum augmented Dickey-Fuller, the explosive test strategy	Throughout the COVID-19 outbreak, west Texas Light crude oil and north sea brent crude oil had a negative financial bubble
Adedeji et al. [40]	March 20, 2020–May 28, 2020	West Texas intermediate, brent, bonny, Daqing	Vector autoregressive (VAR) method	The influence of the COVID-19 pandemic on bonny and Daqing oil prices accounted for the smallest shares of fluctuation, while the effect on BRENT and WTI is even smaller
Bourghelle et al. [48]	January 2, 2014–April 1, 2020	West Texas index, economic policy uncertainty index, equity market-related EPU index	Vector autoregressive (VAR) framework	The disease outbreak oil shocks had a significant effect on oil price fluctuations
Khan et al. [72]	January 2020–May 2021	West intermediate Texas, brent oil, natural gas, heating oil	Quantile-on-quantile method	COVID-19 has a generally negative impact on energy prices across all quantiles
Maneejuk et al. [44]	December 29, 2019–December 30, 2020	Natural gas, gasoline, heating oil, coal, and brent crude oil	Generalized autoregressive conditional heteroskedasticity (GARCH), Markov switching dynamic copula	Energy markets react the same way to both positive and negative occurrences of COVID-19
Nyga-Łukaszewska and Aruga [39]	January 1, 2020–June 2, 2020,	WTI, Platts Dubai crude oil prices, Henry hub, Platts Japan Korea marker prices	Auto-regressive distributive lag (ARDL)	The COVID-19 pandemic in the United States had a statistically detrimental effect on crude oil prices while having a positive impact on gas prices
Le et al. [24]	January 17, 2020–September 14, 2020	WTI oil price, brent, trade-weighted US dollar index, MSCI world index, FTSE all-world index, S&P Global 100 index	ARDL bounds testing procedure	The fall in WTI prices is attributed to increases in COVID-19 instances, US economic policy uncertainty index, and the Chicago board options exchange (CBOE) volatility index (VIX)

Table 1: Continued.

Author (s)	Period	Variables	Methodology	Outcomes
Ahundjanov et al. [43]	January 22, 2020–July 2, 2020	Brent, west Texas intermediate, New York harbor, Dow Jones US oil and gas	Structural vector autoregressive (SVAR) model	A unit rise in COVID-19 global search interest leads to a cumulative reduction of 0.083 percent and 0.104 percent in the Dow Jones US oil, and gas total index and New York harbor conventional gasoline, respectively
Li et al. [33]	December 1, 2019–March 25, 2022.	WTI crude oil futures prices	Multivariate wavelet	The COVID-19 pandemic is less of a concern to the people in the US and Canada than the fall in the WTI and worldwide stock markets
Chatziantoniou et al. [56]	January 17, 1997–December 11, 2020	WTI, brent, heating oil, kerosene, propane, and gasoline	Conditional autoregressive value-at-risk (CAViaR), TVP-VAR	With substantial crisis events, connectivity increases

Source: author's own work.

rise in energy prices. The world economy is significantly impacted by the pandemic caused by COVID-19 disease, and the effects will be long-term and will depend on the intensity of the pandemic. In our quantitative study, we use daily data from July 1, 2021, to December 21, 2021, namely the period that incorporates the fourth wave of the COVID-19 pandemic.

To achieve the proposed goals, we picked the number of new COVID-19 cases registered in Europe and globally as COVID-19 variables. We assume that the evolution of the number of new COVID-19 cases will better capture the pandemic's impact on the energy market, where we used various indices that seize the price of electricity and gas. In addition, we intended to include a Romanian stock market index that tracks the evolution of companies in the energy sector, as well as a survey of the composite index's largest companies. The selected measures are presented in Table 2.

Therefore, a wide array of variables has been selected from the Refinitiv Eikon database alike Ashok et al. [26], which allows the achievement of our research objective, namely, indices on the stock market that describe the energy sector (e.g., EEX-B, EEX-P, APX, and LNGI), along with the specific Romanian energy market index BET-NG. In addition, we have included the daily returns of several leading Romanian companies listed on the Bucharest Stock Exchange (BSE) that operate in the energy field (e.g., SNG, EL, TGN, and TEL). COVID-19 pandemic is measured through daily recent reported cases worldwide (CNW) alike Villarreal-Samaniego [2], Atri et al. [3], Le et al. [24], Jeris and Nath [37], Ahundjanov et al. [43], Maneejuk et al. [44] and in Europe (CNE).

3.2. Quantitative Analysis Strategy. To explore how the COVID-19 pandemic affects the Romanian energy market, more specifically the price of energy and the price of gas, we will employ a variety of econometric tools such as: (1) stationarity analysis, (2) generalized autoregressive conditional heteroskedasticity (GARCH) estimation, (3) autoregressive distributed lag (ARDL) models, (4) vector autoregressive (VAR) models, (5) the Granger causality test.

First, the Augmented Dickey–Fuller Unit Root (ADF) test will be used to verify the nonstationarity of our variables similar to Villarreal-Samaniego [2], Atri et al. [3], Bildirici et al. [8], Wu and Ma [9], Li et al. [10], Wang et al. [21], Wang et al. [34], Geyikçi [41], Ahundjanov et al. [43], Amamou and Bargaoui [49], Lin and Su [50], Zhang and Wang [57], Albulescu [66], Albulescu [67]. Specifically, nonstationary variables lead to inadequate results, which means insignificant results. The confirmation of the stationarity of the selected data is performed through the ADF stationarity test, being the regular test employed to confirm the stationarity of a data series. The null hypothesis of the ADF test assumes that the variable has a unit root, and thus the measure is not stationary. The ADF test involves estimating the equation as follows:

$$\Delta m_t = \alpha + \beta t + q\omega_t + \sum_{j=1}^{k} \gamma_j \Delta m_{t-j} + \varepsilon_t, \quad t = 1, \ldots, T, \quad (1)$$

where t represents the time trend, T is sample length and k is the length of the lag in the dependent variable. Nevertheless, the ADF test is based on a linear assumption, which can lead to inaccurate results [8]. Thus, to check the robustness of our results, further unit root tests alike Kwiatkowski-Phillips-Schmidt-Shin and Zivot–Andrews with one break will be applied in line with Zhang, Farnoosh [7].

Secondly, volatility clustering is a method of identifying market volatility. Due to the pandemic news outburst, the market typically encounters an unstable phase prior to returning to regularity [52]. In order to explore the volatility of the selected series, the GARCH (p, q) model will be

Table 2: Variables' description.

Variables	Description
CNW	New cases of COVID-19 pandemic worldwide
CNE	New cases of COVID-19 pandemic in Europe
BET-NG	The daily return of BET-NG–is a sectoral index that reflects the evolution of companies listed on the regulated market of the Bucharest stock exchange that have the main field of activity energy and related utilities
SNG	The daily return of S.N.G.N. ROMGAZ S.A.–company that has a vast experience in the field of exploration and production of natural gas, being one of the largest producers and main suppliers of natural gas in Romania
EL	The daily return of electrica–is the only company in Romania listed in the field of electricity distribution and supply
TGN	The daily return of SNTGN Transgaz SA–is the technical operator of the national transport system (NTS) natural gas that ensures conditions of safety, efficiency, competitiveness, and in compliance with European standards of performance and environment, the transport of over 90% of natural gas consumed in Romania
TEL	The daily return of CNTEE trans electrica SA–is already recognized on a national scale and globally as a strong company, with a strategic role in the Romanian electricity market and an essential participant in the regional electricity market
EEX-B	The daily return of the physical electricity index (Phelix)–refers to the base load (Phelix base) price index published daily on the power spot market for the German/Austrian market area
EEX-P	The daily return of the physical electricity index (Phelix)–refers to the peak load (Phelix peak) price index published daily on the power spot market for the German/Austrian market area
APX	The daily return of the Amsterdam power exchange (APX) electricity Netherlands average all hours
LNGI	The daily return of the London natural gas index United Kingdom pence per 100000 British thermal units

Source: author's own work.

considered alike [4], Szczygielski et al. [5], Wu and Ma [9], Maneejuk et al. [44], Iglesias and Rivera-Alonso [51], Zhang and Wang [57], which shows the following general form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{2}$$

where p is the order of the GARCH terms and q is the order of the ARCH terms.

Thirdly, in case we find out both stationary and non-stationary variables, consistent with Villarreal-Samaniego [2], Atri et al. [3], Li et al. [10], Le et al. [24], Jeris and Nath [37], Nyga-Łukaszewska and Aruga [39], Geyikçi [41], Albulescu [66], Albulescu [67], the ARDL approach will allow the study of both short-term and long-term relationships between COVID-19 variables and the energy market. The ARDL approach exhibits several advantages over different cointegration models in quantitative literature [37]. First, the autoregressive distributed lag model (ARDL) and the limit testing methodology will be used due to its permission to apply a mixture of variables I (0) and I (1) [2, 37, 41]. Choosing the appropriate ARDL model will allow us exploring the relationships that are established between variables, so it is imperative to select the proper number of offsets. Therefore, the Akaike information criteria (AIC) will be examined to decide on the optimal gaps for the variables included in the ARDL model alike [2]. Second, this method abridges the study of the link among the response and input variables through OLS regressions. Third, when contrasted to other methodologies, the ARDL technique is more effective for small samples, which is particularly critical for this research [2, 37, 41]. Not least, the ARDL specification permits simultaneous estimation of both long-run and short-run parameters [37, 41].

Specifically, an *ARDL* $(p, q_1, \ldots, q_k)$ is a least squares regression containing lags of the dependent (p) and explanatory variables $(q_1, \ldots, q_k)$. The general specification of an *ARDL* (p, q) model is depicted below:

$$\begin{aligned} H_t = \mu + \beta_0 K_t + \beta_1 K_{t-1} + \cdots + \beta_q K_{t-q} + \delta_1 H_{t-1} \\ + \cdots + \delta_p H_{t-p} + u_t. \end{aligned} \tag{3}$$

Fourthly, the vector autoregression (VAR) framework is considered due to its common practice for interdependent time series prediction systems and for analyzing the dynamic impact of random perturbations on the system of variables. The equation for the VAR model is depicted below, consistent with Wu and Ma [9], Bourghelle et al. [48]:

$$x_t = a_1 x_{t-1} + \cdots + a_p x_{t-p} + bn_t + \epsilon_t, \tag{4}$$

where x_t is a k vector of endogenous variables, n_t is a d vector of exogenous variables, $a_1, \ldots, a_p$ and b are matrices of coefficients to be estimated, and ϵ_t is a vector of innovations.

Not least, causality between variables will be examined through the Granger causality test, like Wu and Ma [9], Bourghelle et al. [48]. The null hypothesis of the test consists of the following statements: h does not cause Granger k and that k does not cause Granger h. There are estimated the following bivariate regressions:

$$\begin{aligned} k_t &= \alpha_0 + \alpha_1 k_{t-1} + \cdots + \alpha_p k_{t-p} + \beta_1 h_{t-1} + \cdots + \beta_p h_{-p} + \epsilon_t, \\ h_t &= \alpha_0 + \alpha_1 h_{t-1} + \cdots + \alpha_p h_{t-p} + \beta_1 k_{t-1} + \cdots + \beta_p k_{-p} + u_t. \end{aligned} \tag{5}$$

4. Empirical Findings

4.1. Summary Statistics. The descriptive statistics of the variables are provided in Table 3. The skewness and kurtosis indicators indicate the deviation in relation to a symmetric distribution around the average, thus suggesting the degree

Table 3: Descriptive statistics of the variables.

Variables	Mean	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability
CNE	231054	108995	0.89	2.44	18.01	0.00
CNW	578864	113085	0.35	2.38	4.50	0.11
BET-NG	0.0001	0.01	−0.74	4.40	21.55	0.00
SNG	0.0012	0.01	−0.82	6.56	79.63	0.00
EL	−0.0020	0.01	−0.75	5.23	37.41	0.00
TEL	−0.0012	0.02	0.48	8.58	165.98	0.00
TGN	−0.0022	0.01	−0.37	4.52	14.75	0.00
EEX-B	0.0124	0.27	0.15	5.49	32.58	0.00
EEX-P	0.0134	0.34	0.10	5.88	43.04	0.00
APX	0.0124	0.19	0.59	6.53	71.43	0.00
LNGI	0.0099	0.06	2.06	43.21	8442.14	0.00

Source: author's own work. Notes: for the definition of variables, please see Table 2.

of flattening or sharpening. A kurtosis greater than the value of three implies that the returns of the indices show heavy tails than the normal distribution. Specifically, the probability of extreme returns is higher than the probability that they are below normal distribution. This feature is called leptokurtic or basically heavy tails. A positive skewness signifies an asymmetric distribution on the right and a negative skewness on the left. For a series with a normal distribution, kurtosis takes the value of three. However, for a value less than three the distribution is flatter than the normal one (e.g., platykurtic), whereas for kurtosis greater than three, the distribution is leptokurtic. According to Table 3, most of the variables exhibit a value of the kurtosis greater than three, thus presenting a leptokurtic distribution, consistent with Bildirici et al. [8], Wu and Ma [9], Wang et al. [36], Geyikçi [41], Bourghelle et al. [48], Dutta et al. [53]. Consequently, extreme negative returns are much more likely to occur than normal distribution forecasts.

The normality of the variable distribution is provided by the Jarque-Bera test. Table 3 also shows the results of the Jarque-Bera test, which indicate that the distribution of the variables is not distributed normally, in line with Villarreal-Samaniego [2], Bildirici et al. [8], Ali et al. [25], Si et al. [28], Wang et al. [36], Mensi et al. [38], Akhtaruzzaman et al. [69], Gharib et al. [71], Khan et al. [72]. Because the Jarque-Bera statistic is significant (except for the number of new cases of COVID-19 registered globally), we reject the null hypothesis of normality. The test values are quite far from the corresponding normal distribution, which supports that the series is not normally distributed. Figure 1 exhibits the density, distribution, and quantile-quantile (QQ) plots. In line with the outcomes reported in Table 3, the distribution of the selected series is dissimilar from the normal one.

The correlations between included variables are plotted in Figure 2. Alike [37], the correlations were reduced. Therefore, our empirical outcomes will not be affected by the multicollinearity issue.

Figure 3 shows the evolution of the number of new cases at the European and global levels due to COVID-19. Cássaro and Pires [73] argued that the number of cases is growing rapidly, which has been achieved by stability later, this mode is called a step function.

Further, the daily evolution of the BET-NG index and the companies listed on BSE are presented in Figure 4. During the third and fourth quarters of 2021, BET-NG, the index of the 10 Romanian companies in the energy and utility sectors, registered a relatively steady evolution. EL, SNG, and TGN, which are among the most traded companies on BSE, had a similar evolution to the BET-NG index, but TEL was marked by slightly more significant episodes of volatility than the rest of the energy companies.

Likewise, the evolution related to the return of the Physical Electricity Index (Phelix), Amsterdam Power Exchange (APX), and London Natural Gas Index is exhibited in Figure 5. Energy prices have witnessed high episodes of volatility compared to the price of natural gas. The return of global activity, as the restrictions imposed by the pandemic and the complete reopening of economies have lifted, has led to a rapid increase in demand for natural gas, both for electricity production and for manufacturing reasons.

4.2. The Outcomes of Time Series Investigation

4.2.1. Stationarity Analysis. Tables 4 and 5 show the outcomes of stationarity analysis for series at the level and in the first difference through the augmented Dickey–Fuller and Kwiatkowski–Phillips–Schmidt–Shin unit root test. A couple of variables are stationary at the first difference (e.g., new cases of COVID-19 worldwide and in Europe) because the probability is above the 1% and 5% relevance level, while some are already stationary (e.g., BET-NG, SNG, EL, TGN, TEL, EEX-B, EEX-P, APX, and LNGI). Alike Bildirici et al. [8], Ali et al. [25], Si et al. [28], Mensi et al. [38], and Yousaf [47], we notice a common integration order of I (0), exception makes the indicators related to the evolution of COVID-19, so in this case, we can reject the null hypothesis and conclude that the series is not stationary.

Further, Table 6 reveals the outcomes of stationarity analysis of the variables with one structural break by means of the Zivot-Andrews unit root test, alike Zhang et al. [7], Le et al. [24]. Accordingly, the occurrence of a structural break in our sample is proved, while the mix integration is strengthened.

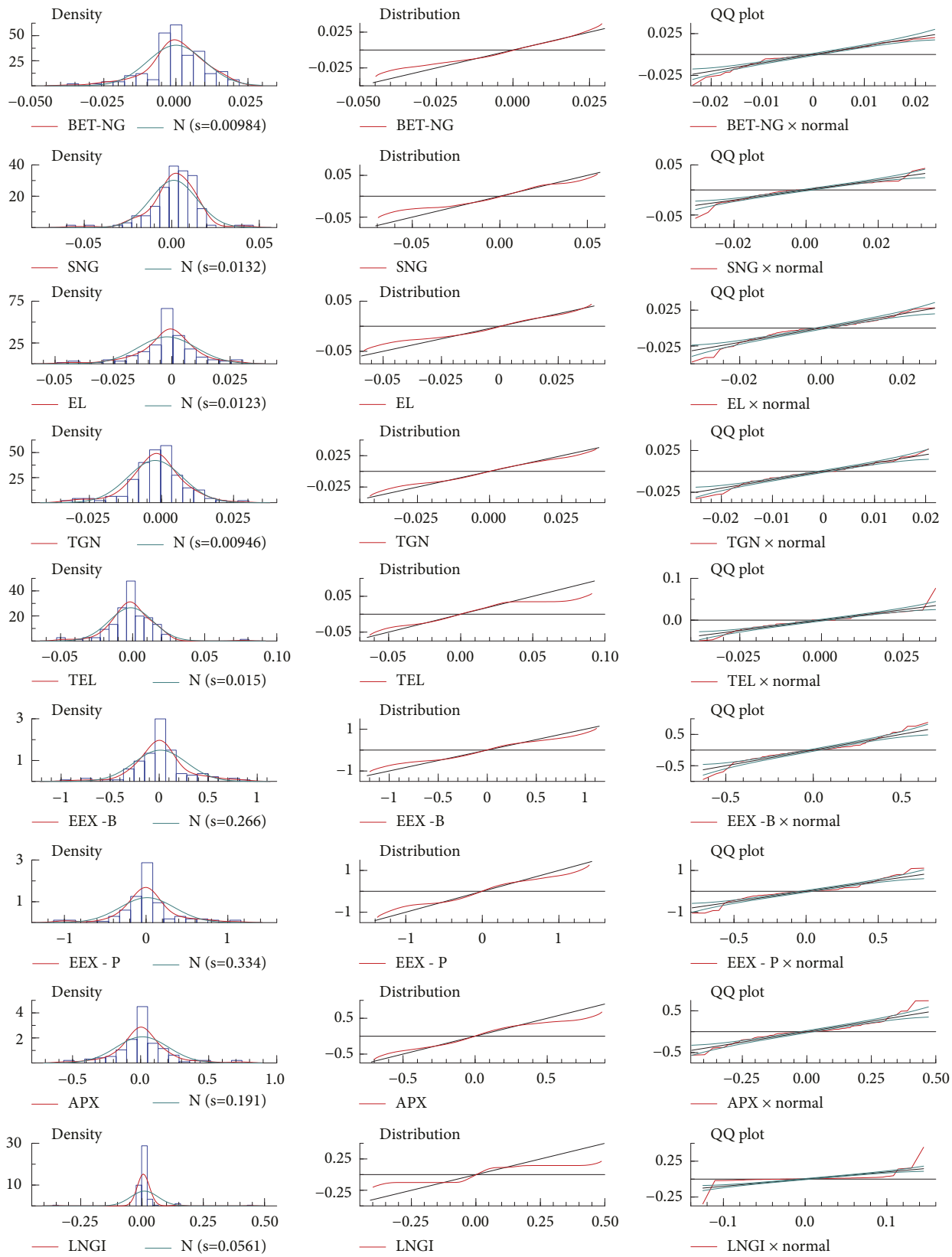

Figure 1: Density, distribution, and QQ plots for daily returns. Source: author's own work. Notes: variables' descriptions are provided in Table 2.

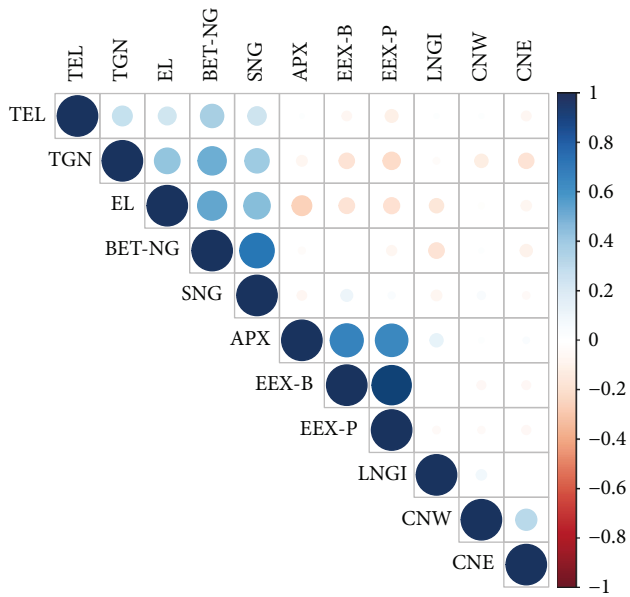

Figure 2: Correlations among selected variables. Source: author's own work. Notes: variables' descriptions are provided in Table 2.

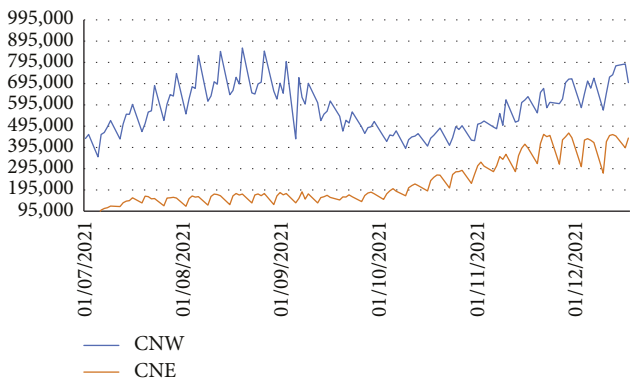

Figure 3: Evolution of COVID-19 pandemic variables. Source: author's own work. Notes: for the definition of variables, please see Table 2.

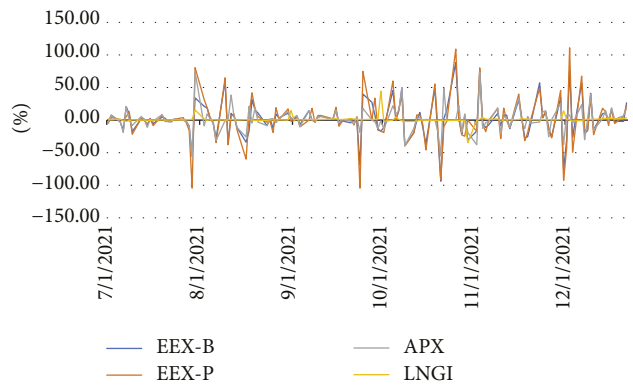

Figure 5: Evolution of energy market. Source: author's own work. Notes: for the definition of variables, please see Table 2.

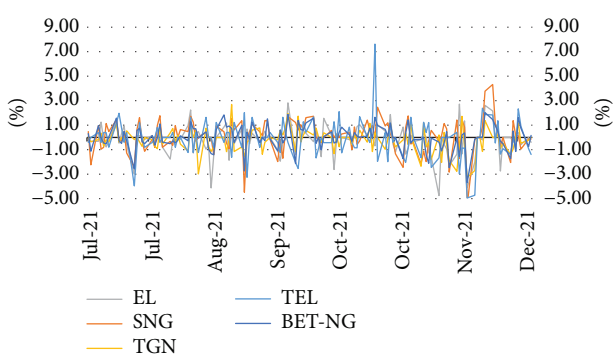

Figure 4: Evolution of BET-NG index and of the companies listed on BSE. Source: author's own work. Notes: for the definition of variables, please see Table 2.

4.2.2. Volatility Examination. Because all Jarque–Bera figures are larger than three as Bildirici et al. [8], Zhang and Wang [57] found, and the distributions of the selected series diverge from normally distributed data; GARCH models are required and appropriate for highlighting the progress of volatility. Further, the autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to test for heteroskedasticity. In this regard, Figure 6 exhibits the plots of ACF and PACF. Thus, the existence of serial correlation is inherent in the correlogram of squared returns, except LNGI for which the GARCH model will not be estimated.

Table 7 reports the findings after estimating the GARCH (1, 1) model. In the case of TEL, the sum of ARCH and GARCH parameters is roughly equal to one (e.g., 0.989732), in line with Napon and Asama [4],

Table 4: The outcomes of the augmented Dickey–Fuller unit root test.

Variables	Level		1st difference	
	t-statistic	Prob.	*t*-statistic	Prob.
BET-NG	−10.96815	0.00000	−8.02504	0.00000
SNG	−9.79747	0.00000	−7.02206	0.00000
EL	−10.89207	0.00000	−8.21217	0.00000
TGN	−11.57374	0.00000	−8.25544	0.00000
TEL	−10.62924	0.00000	−7.73848	0.00000
EEX-B	−9.28420	0.00000	−10.03859	0.00000
EEX-P	−9.26251	0.00000	−7.88023	0.00000
APX	−3.85224	0.00330	−9.07506	0.00000
LNGI	−10.80412	0.00000	−6.78637	0.00000
D (CNW)	−1.05455	0.73150	−6.46469	0.00000
CNE	1.49212	0.99920	−3.17439	0.02410

Source: author's own work. Notes: null hypothesis: each series has a unit root. Intercept included in test equation. Lag length: automatic selection based on Akaike info criterion. Test critical values: 1% level: −3.484198; 5% level: −2.885051; 10% level: −2.579386. For the definition of variables, please see Table 2.

Table 5: The outcomes of the Kwiatkowski–Phillips–Schmidt–Shin unit root test.

Variables	Level LM-stat.	1st difference LM-stat.
BET-NG	0.12317	0.10802
SNG	0.05132	0.27447
EL	0.07358	0.22224
TGN	0.33589	0.09240
TEL	0.09570	0.03197
EEX-B	0.26477	0.10671
EEX-P	0.25460	0.10521
APX	0.30014	0.14376
LNGI	0.06838	0.33024
D (CNW)	0.11972	0.09233
CNE	1.17286	0.13543

Source: author's own work. Notes: null hypothesis: each series is stationary. Intercept included in test equation. Asymptotic critical values: 1% level: 0.739000; 5% level: 0.463000; 10% level: 0.347000. For the definition of variables, please see Table 2.

Table 6: The outcomes of the Zivot–Andrews unit root test.

Variables	Level			1st difference		
	t-statistic	Prob.	Chosen breakpoint	*t*-statistic	Prob.	Chosen breakpoint
BET-NG	−11.60250	0.01458	10/29/2021	−10.16953	0.36943	9/28/2021
SNG	−10.09328	0.10998	10/28/2021	−8.84880	0.39676	11/11/2021
EL	−11.14620	0.03227	10/28/2021	−7.83243	0.31284	11/22/2021
TGN	−12.34624	0.00983	11/05/2021	−9.03870	0.11226	11/24/2021
TEL	−10.82827	0.09506	10/26/2021	−8.09940	0.04814	10/22/2021
EEX-B	−9.51280	0.04077	10/25/2021	−9.62517	0.18050	10/22/2021
EEX-P	−9.47839	0.21478	10/11/2021	−11.07540	0.17081	10/22/2021
APX	−8.48267	0.03560	10/14/2021	−10.47777	0.08917	10/08/2021
LNGI	−11.55259	0.00709	10/07/2021	−8.20949	0.02625	10/04/2021
D (CNW)	−9.57362	0.00002	8/23/2021	−15.98563	0.34203	9/16/2021
CNE	−2.45574	0.00130	10/19/2021	−6.62953	0.02393	10/06/2021

Source: author's own work. Notes: null hypothesis: each series has a unit root with a structural break in the intercept. Break included in the intercept. 1% critical value: −5.34.5% critical value: −4.93.10% critical value: −4.58. For the definition of variables, please see Table 2.

Bildirici et al. [8]. Hence, at time t, a shock wave will last longer. Specifically, the conditional variance is persistent consistent with Maneejuk et al. [44], Iglesias, and Rivera-Alonso [51]. The findings, however, show the existence of a mean-reverting process because the sum of the ARCH and GARCH effects is less than one. However, in the case

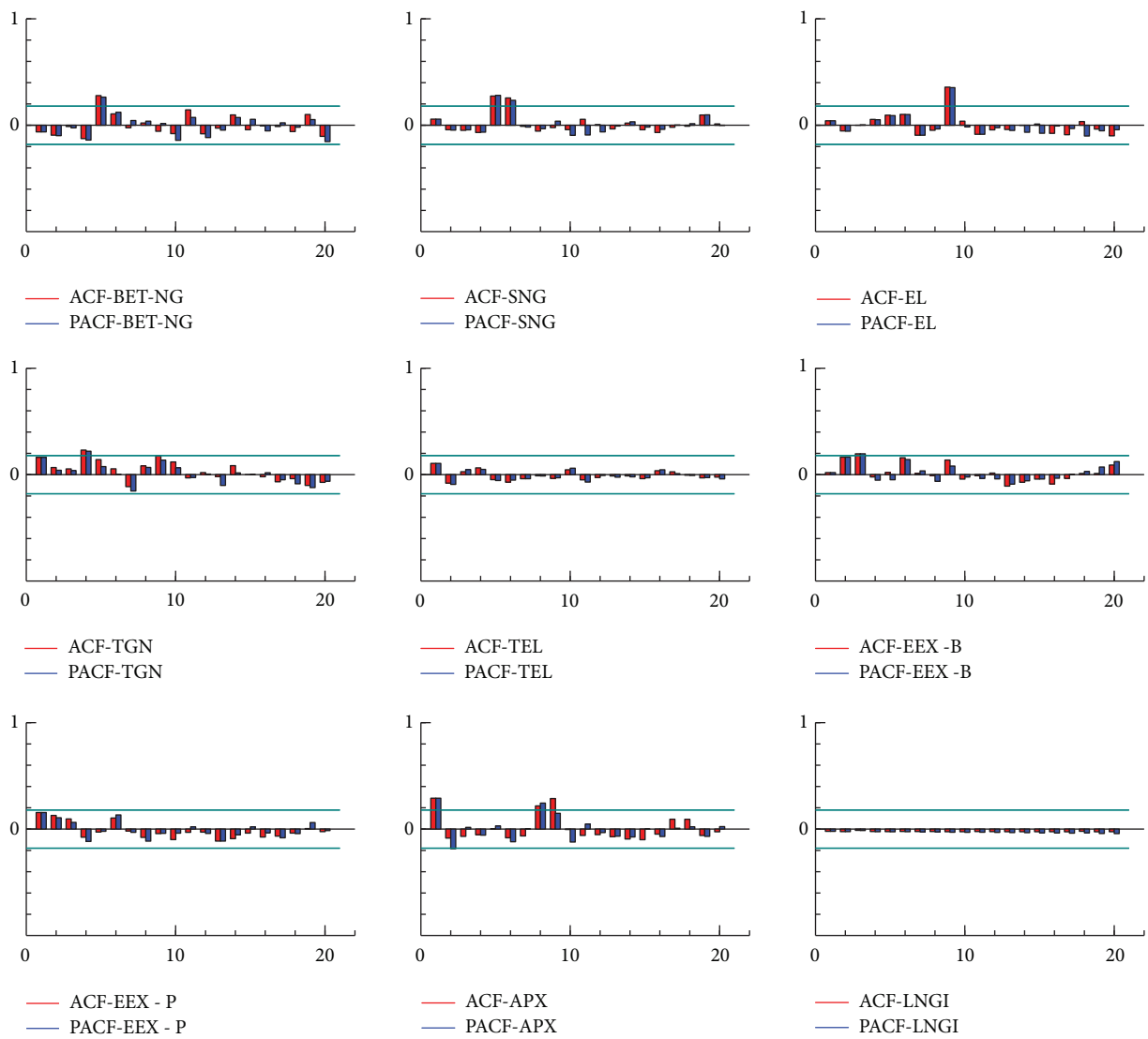

Figure 6: Plots of autocorrelation function (ACF) and partial autocorrelation function (PACF) for squared returns. Source: author's own work. Notes: the lag length was set to 20. Variables' descriptions are provided in Table 2.

of EEX-B, EEX-P, and APX, the sum of parameters is larger than one, thus suggesting that the conditional variance process is explosive.

We estimated the conditional volatilities (CV) after assessing the GARCH model (1, 1), as shown in Figure 7. Among the Romanian companies operating in the energy field, we notice that the highest CV was registered by the major performers in the energy allocation and supply market in Romania, respectively Electrica.

4.2.3. ARDL Estimation Results. Since the stationarity test confirmed that the selected variables are integrated in the order of 0 and 1, in line with Le et al. [24], this fact allows us to consider the approach of the ARDL analysis technique. This method permits the cointegration examination of variables that are stationary and non-stationary. For the proper choice of the ARDL model that would allow us to research the relationships that are established between the variables, it is imperative to choose the correct number of offsets. Therefore, alike Nyga-Łukaszewska and Aruga [39], we will analyze the Akaike Information Criteria (AIC) to select the optimal offsets for the variables included in the ARDL model. We will apply the criteria graph, which will indicate the right lags for the ARDL model, and the lowest value is preferred. Figure 8 shows the plots of criteria graph for each ARDL model which considers every energy variable (e.g., BET-NG, SNG, EL, TGN, TEL, EEX-B, EEX-P, APX, and LNGI), as well as the number of new cases at European and global level due to COVID-19. The horizontal axis of each chart represents the ARDL models estimated, and the vertical axis shows the AIC value of the models. The top 20 results are presented in the criteria graph.

The figures in Table 8 signify the results for the ARDL bound test for cointegration. There are provided two critical values for the cointegration test: the lower critical bound

Table 7: The outcomes of the GARCH (1, 1) model.

Dependent variable: BET-NG					*Dependent variable: SNG*				
Variable	Coefficient	Std. error	*z*-statistic	Prob.	Variable	Coefficient	Std. error	*z*-statistic	Prob.
C	0.000512	0.000777	0.658956	0.5099	C	0.002226	0.000964	2.30789	0.021
	Variance equation					Variance equation			
C	$4.21E-05$	$4.80E-05$	0.876802	0.3806	C	$9.67E-05$	0.000181	0.533331	0.5938
RESID $(-1)^2$	−0.07493	0.068867	−1.088046	0.2766	RESID $(-1)^2$	−0.04884	0.072398	−0.674602	0.4999
GARCH (−1)	0.656334	0.456352	1.43822	0.1504	GARCH (−1)	0.542073	0.916932	0.591181	0.5544
T-DIST. DOF	5.061521	3.142783	1.610522	0.1073	T-DIST. DOF	3.452623	1.250747	2.760448	0.0058
ARCH + GARCH	0.581404				ARCH + GARCH	0.493233			
R-squared	−0.001889	Mean dependent var		$8.42E-05$	*R*-squared	−0.006586	Mean dependent var		0.001153
Adjusted *R*-squared	−0.001889	S.D. dependent var		0.009884	Adjusted *R*-squared	−0.006586	S.D. dependent var		0.013269
S.E. of regression	0.009894	Akaike info criterion		−6.409628	S.E. of regression	0.013313	Akaike info criterion		−5.904976
Sum squared resid	0.01204	Schwarz criterion		−6.295907	Sum squared resid	0.0218	Schwarz criterion		−5.791255
Log likelihood	402.3969	Hannan–Quinn criterion.		−6.363432	Log likelihood	371.1085	Hannan–Quinn criterion.		−5.85878
Durbin-Watson stat	1.988924				Durbin-Watson stat	1.7568			
Dependent variable: EL					*Dependent variable: TGN*				
Variable	Coefficient	Std. error	*z*-statistic	Prob.	Variable	Coefficient	Std. error	*z*-statistic	Prob.
C	$-8.80E-06$	0.000686	−0.012818	0.9898	C	−0.001581	0.000705	−2.242621	0.0249
	Variance equation					Variance equation			
C	0.000349	0.008276	0.042186	0.9664	C	$6.14E-06$	$5.86E-06$	1.048826	0.2943
RESID $(-1)^2$	−1.784395	42.03255	−0.042453	0.9661	RESID $(-1)^2$	0.075788	0.074665	1.015035	0.3101
GARCH (−1)	0.987717	0.018899	52.26289	0	GARCH (−1)	0.874339	0.102292	8.547464	0
T-DIST. DOF	2.024389	0.58422	3.465116	0.0005	T-DIST. DOF	4.349566	2.444385	1.779412	0.0752
ARCH + GARCH	−0.796678				ARCH + GARCH	0.950127			
R-squared	−0.025806	Mean dependent var		−0.001991	*R*-squared	−0.004356	Mean dependent var		−0.002206
Adjusted *R*-squared	−0.025806	S.D. dependent var		0.012388	Adjusted *R*-squared	−0.004356	S.D. dependent var		0.009498
S.E. of regression	0.012547	Akaike info criterion		−6.171115	S.E. of regression	0.009519	Akaike info criterion		−6.559459
Sum squared resid	0.019363	Schwarz criterion		−6.057394	Sum squared resid	0.011145	Schwarz criterion		−6.445738
Log likelihood	387.6091	Hannan–Quinn criterion.		−6.124919	Log likelihood	411.6864	Hannan–Quinn criterion.		−6.513262
Durbin–Watson stat	1.93045				Durbin–Watson stat	2.091561			
Dependent variable: TEL					*Dependent variable: EEX-B*				
Variable	Coefficient	Std. error	*z*-statistic	Prob.	Variable	Coefficient	Std. error	*z*-statistic	Prob.
C	−0.000856	0.000926	−0.924074	0.3554	*C*	0.006158	0.010772	0.571666	0.5675
	Variance equation					Variance equation			
C	$5.27E-06$	$1.80E-06$	2.936929	0.0033	*C*	0.006022	0.014758	0.408033	0.6832
RESID $(-1)^2$	−0.05078	0.016305	−3.114411	0.0018	RESID $(-1)^2$	1.51924	4.01251	0.378626	0.705
GARCH (−1)	1.040512	0.01393	74.69655	0	GARCH (−1)	0.67125	0.110199	6.091232	0
T-DIST. DOF	5.767578	3.219184	1.791627	0.0732	T-DIST. DOF	2.200545	0.599848	3.668503	0.0002
ARCH + GARCH	0.989732				ARCH + GARCH	2.19049			
R-squared	−0.000593	Mean dependent var		−0.001222	*R*-squared	−0.000556	Mean dependent var		0.012439
Adjusted *R*-squared	−0.000593	S.D. dependent var		0.015068	Adjusted *R*-squared	−0.000556	S.D. dependent var		0.267469
S.E. of regression	0.015073	Akaike info criterion		−5.758566	S.E. of regression	0.267543	Akaike info criterion		−0.16669
Sum squared resid	0.027944	Schwarz criterion		−5.644845	Sum squared resid	8.804247	Schwarz criterion		−0.052969
Log likelihood	362.0311	Hannan–Quinn criterion.		−5.71237	Log likelihood	15.3348	Hannan–Quinn criterion.		−0.120494
Durbin-Watson stat	1.930154				Durbin-Watson stat	2.342452			
Dependent variable: EEX-P					*Dependent variable: APX*				
Variable	Coefficient	Std. error	*z*-statistic	Prob.	Variable	Coefficient	Std. error	*z*-statistic	Prob.
C	0.005919	0.011652	0.507994	0.6115	*C*	0.006374	0.010206	0.624526	0.5323
	Variance equation					Variance equation			
C	4.01294	5739.496	0.000699	0.9994	*C*	0.011582	0.045943	0.252091	0.801
RESID $(-1)^2$	492.9499	705091.9	0.000699	0.9994	RESID $(-1)^2$	0.641769	2.500938	0.256611	0.7975

Table 7: Continued.

Dependent variable: BET-NG					*Dependent variable: SNG*				
Variable	Coefficient	Std. error	*z*-statistic	Prob.	Variable	Coefficient	Std. error	*z*-statistic	Prob.
GARCH (−1)	0.758657	0.086541	8.766479	0	GARCH (−1)	0.787782	0.11503	6.848478	0
T-DIST. DOF	2.000299	0.427798	4.675804	0	T-DIST. DOF	2.148645	0.643148	3.340823	0.0008
ARCH + GARCH	493.708557				ARCH + GARCH	1.429551			
R-squared	−0.000496	Mean dependent var		0.013354	*R*-squared	−0.001009	Mean dependent var		0.012429
Adjusted *R*-squared	−0.000496	S.D. dependent var		0.335083	Adjusted *R*-squared	−0.001009	S.D. dependent var		0.191365
S.E. of regression	0.335166	Akaike info criterion		0.157424	S.E. of regression	0.191462	Akaike info criterion		−0.736736
Sum squared resid	13.81739	Schwarz criterion		0.271145	Sum squared resid	4.508874	Schwarz criterion		−0.623015
Log likelihood	−4.760306	Hannan–Quinn criterion.		0.20362	Log likelihood	50.67763	Hannan–Quinn criterion.		−0.69054
Durbin–Watson stat	2.542814				Durbin–Watson stat	2.697083			

Source: author's own work. Notes: method: ML ARCH–student's *t* distribution (BFGS/Marquardt steps). Sample: 7/01/2021–12/21/2021. Included observations: 124. For the definition of variables, please see Table 2.

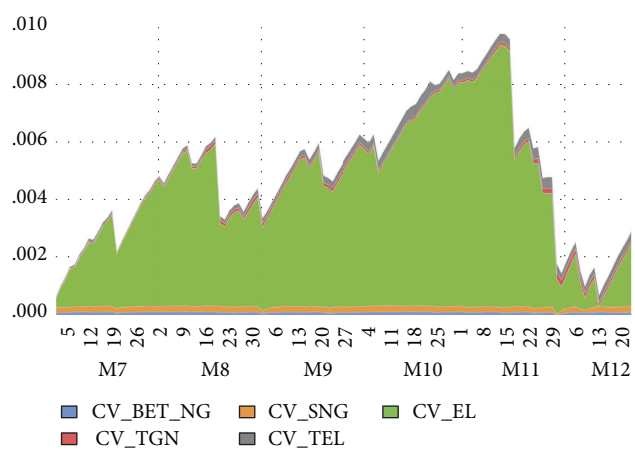

Figure 7: Conditional volatility (CV) plot of Romanian stock market index and energy companies. Source: author's own work. Notes: variables' descriptions are provided in Table 2.

assumes all the variables are *I* (0), meaning that there is no cointegration and the upper bound assumes that all the variables are *I* (1), meaning that there is cointegration among the variables. If the value of the *F*-statistic is more than the critical value of bounds, it indicates the long-run relationship between variables. Accordingly, in all cases, the value of the *F*-statistical test is higher than the limit of 1%, which suggests that there is a long-term relationship between variables. Hence, the null hypothesis is rejected, which means that the variables in all estimated models are cointegrated. As such, we notice cointegration relationships between COVID-19 and BET-NG, SNG, EL, TGN, TEL, EEX-B, EEX-P, APX, and LNGI.

Table 9 shows the results of the long-term relationship between variables for COVID-19 new cases in Europe and worldwide and energy market-specific variables. The quantitative outcomes provide support for no impact of the number of new cases of COVID-19 in Europe and globally on the price of energy, natural gas, the BET-NG index, and most of the companies operating in the energy field in Romania. However, there is noticed a positive long-term impact of the number of new cases in the EU and globally on TGN.

Table 10 shows the short-run impact of pandemic on the energy market. For all energy market variables is registered a coefficient of the error correction term (*CointEq*(−1)) which is negative and significant at the 5% level of significance. Consequently, the negative and significant error correction term, which indicates the speed of conversion, exhibits that on the next day, the dependent variable will reach equilibrium with a speed of between 87% and 229%. Also, the short-term results provided in Table 10 show a positive impact of the new cases of COVID-19 registered in Europe on the evolution of the TEL share price. Therefore, an increase in the number of new cases of COVID-19 in Europe during the period under review leads to an increase in the price of TEL. Such a relationship was also identified in the case of TGN, where the new number of COVID-19 cases both in Europe and globally exerts a positive impact on the share price. Another outstanding result identified from these ARDL models is that, in the short term, the outcomes show a negative impact of new cases of COVID-19 disease in Europe on the variable EEX-B–proxy variable for the price of electricity.

Further, alike Jeris and Nath [37], Geyikçi [41], this study applied cumulative sum (CUSUM) and cumulative sum of the squares (CUSUM of Squares) to confirm the stability of the long-run and short-run parameters, respectively the reliability and stability of the examined models. While the cumulative sum of squares test detects abrupt changes from the constancy of the regression coefficient, the cumulative sum test captures systematic variations in the regression coefficients [74]. Under the null hypothesis, the regression coefficients remain constant over time, being equal (or stable) in all sequential subsamples Ploberger and Krämer [75]. Hence, the estimated models are stable and there is no structural break in the observed time series, if the null

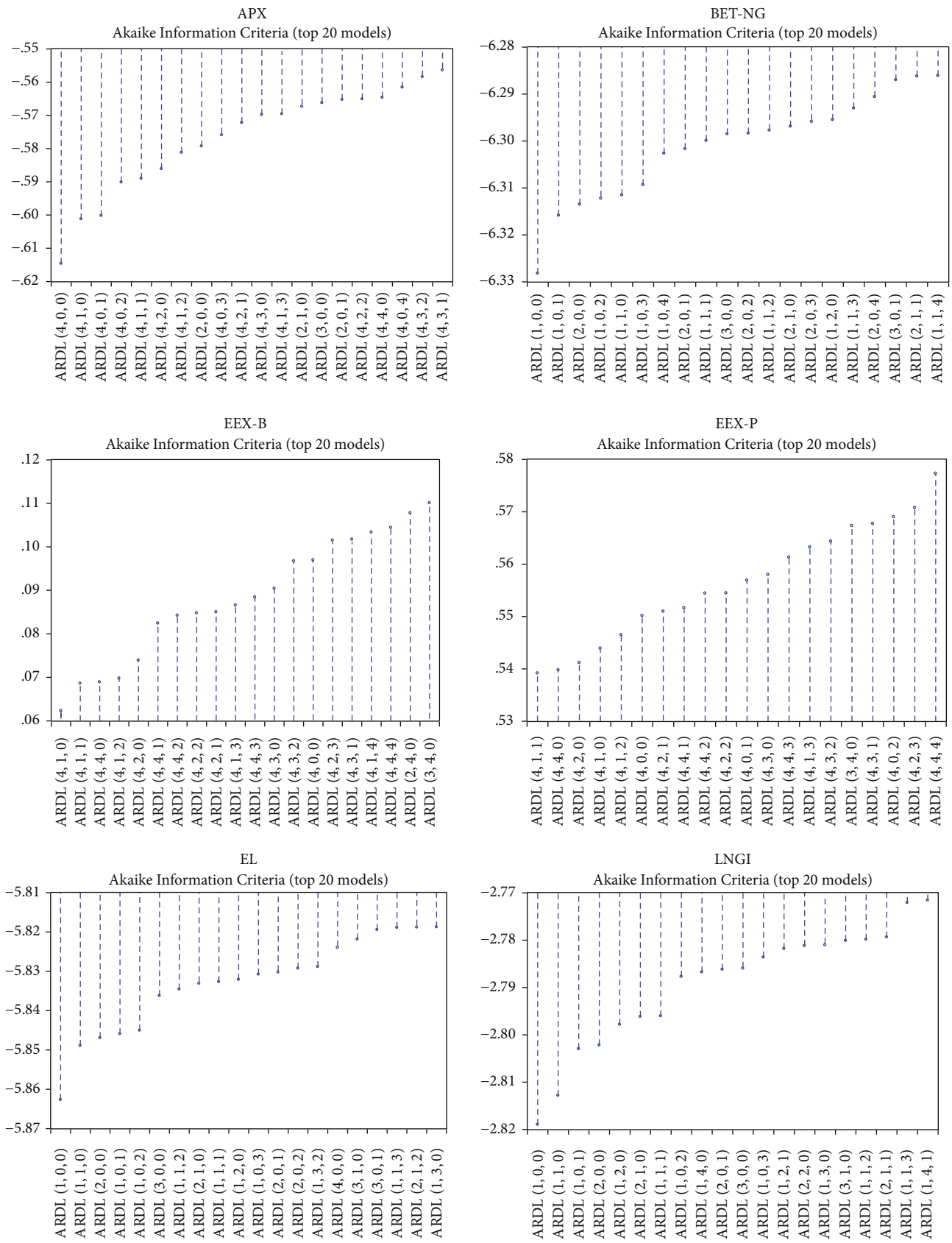

Figure 8: Continued.

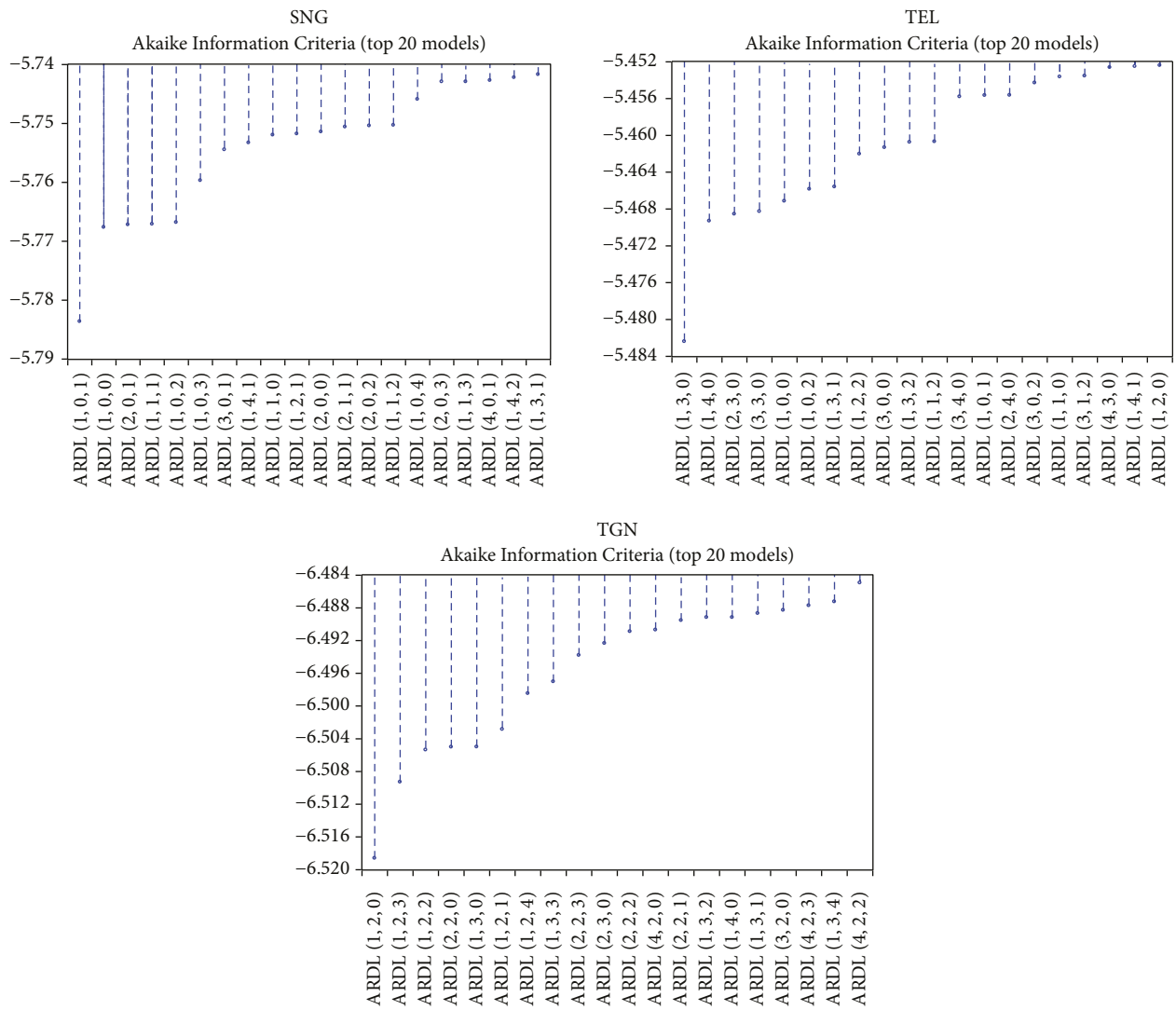

Figure 8: Akaike information criteria (AIC). Source: author's own work. Notes: for the definition of variables, please see Table 2.

hypothesis is valid [76]. Contrarily, the alternative assumption is that the regression coefficients fluctuate during the course of the sample. Nevertheless, the test is commonly questioned on the grounds that it is quite straightforward and does not request a priori information regarding the timing of the structural change [78]. Concretely, these tests produce a diagram by recurrently computing the regression coefficients and residuals [76]. For the stability of the estimated outcomes, the graph should maintain the critical values.

The results of CUSUM and CUSUM of squares are plotted in Figure 9. As far as the CUSUM test is concerned, all the models are stable as the CUSUM blue line is within the 5% significance boundaries illustrated by red dotted lines. Howbeit, the CUSUM test is less powerful because the confidence interval of the test is approximated [77]. In addition, the CUSUM of Squares test shows the stability of APX, BET-NG, EEX-P, and TGN models, but EEX-B, EL, LNGI, SNG, and TEL models are unstable as the CUSUM of Squares blue line crosses the 5% boundary. However, although it is known that the CUSUM of Squares test statistic is distributed as a beta random variable, there should be acknowledged that the confidence interval of the test is also approximated [77].

Further, even though several models are unstable as pointed out by Figure 9, Table 11 provides supplementary diagnostic tests in order to check for robustness. To avoid the serial correlation problem (the association among included variables and its lagged value), the Breusch-Godfrey LM test for autocorrelation (presence of autocorrelation in the null hypothesis) was conducted, while heteroscedasticity was examined by Breusch-Pagan-Godfrey test. Accordingly, the

Table 8: The results of the ARDL bounds test for the model environment and COVID-19.

Test statistic: *F*-statistic		
BET-NG	40.32473	
SNG	33.30209	
EL	39.27895	
TGN	52.79222	
TEL	40.24938	
EEX-B	25.06441	
EEX-P	25.75187	
APX	23.92644	
LNGI	38.06681	
	Critical value bounds	
Significance	*I*0 bound	*I*1 bound
10%	3.17	4.14
5%	3.79	4.85
2.50%	4.41	5.52
1%	5.15	6.36

Source: author's own work. Notes: null hypothesis: no long-run relationships exist. For the definition of variables, please see Table 2.

Table 9: ARDL long-term term coefficients.

Variables	Coefficient	Std. error	*t*-statistic	Prob.
APX				
CNE	0	0	0.800675	0.425
D (CNW)	0	0	−0.22699	0.8208
BET-NG				
CNE	0	0	−0.99716	0.3207
D (CNW)	0	0	0.314219	0.7539
EEX-B				
CNE	0	0	0.629579	0.5303
D (CNW)	0	0	−0.43845	0.6619
EEX-P				
CNE	0	0	0.671389	0.5034
D (CNW)	0	0	−1.31788	0.1903
EL				
CNE	0	0	−0.82507	0.411
D (CNW)	0	0	0.827637	0.4095
LNGI				
CNE	0	0	0.110985	0.9118
D (CNW)	0	0	0.012388	0.9901
SNG				
CNE	0	0	−0.73428	0.4642
D (CNW)	0	0	1.504202	0.1352
TEL				
CNE	0	0	−1.35105	0.1794
D (CNW)	0	0	0.221226	0.8253
TGN				
CNE	0	0	−2.46409	0.0152
D (CNW)	0	0	−2.27302	0.0249

Source: author's own work. Notes: for the definition of variables, please see Table 2.

hypothesis of no serial correlation between variables and its lagged value is rejected at a 5% level of significance (Prob. Chi-Square > 0.05), except for the EEX-P model. In addition, the probability associated with the Chi-Square value is above the 0.05 significance level signifying that the assumption of homoscedasticity fails to be rejected, except EEX-B, EEX-P, and SNG models. Therefore, the errors of the EEX-B, EEX-P, and SNG models are not homoscedastic.

Table 10: ARDL cointegrating and short-term coefficients.

Variables	Coefficient	Std. error	*t*-statistic	Prob.
Dependent variable: APX				
D(APX(−1))	0.809048	0.227774	3.551977	0.0006
D(APX(−2))	0.434999	0.163033	2.668164	0.0087
D(APX(−3))	0.253036	0.091628	2.761563	0.0067
D(CNE)	0	0	0.795941	0.4277
D(D(CNW))	0	0	−0.22721	0.8207
CointEq(−1)	−2.297643	0.272947	−8.41792	0
Dependent variable: BET-NG				
D(CNE)	0	0	−0.99377	0.3224
D(D(CNW))	0	0	0.314607	0.7536
CointEq(−1)	−1.003723	0.09165	−10.9517	0
Dependent variable: EEX-B				
D(EEX-B(−1))	0.833263	0.190063	4.384153	0
D(EEX-B(−2))	0.464822	0.140376	3.311257	0.0013
D(EEX-B(−3))	0.313867	0.087614	3.582395	0.0005
D(CNE)	−0.000001	0.000001	−2.19195	0.0305
D(D(CNW))	0	0	−0.43939	0.6612
CointEq(−1)	−2.033893	0.235973	−8.61918	0
Dependent variable: EEX-P				
D(EEX-P(−1))	0.839216	0.208358	4.027771	0.0001
D(EEX-P(−2))	0.514926	0.152479	3.377025	0.001
D(EEX-P(−3))	0.279896	0.089542	3.125875	0.0023
D(CNE)	−0.000002	0.000001	−1.75091	0.0827
D(D(CNW))	0	0	−0.75757	0.4503
CointEq(−1)	−2.206487	0.257442	−8.57081	0
Dependent variable: EL				
D(CNE)	0	0	−0.82438	0.4114
D(D(CNW))	0	0	0.833004	0.4065
CointEq(−1)	−0.99039	0.091465	−10.8281	0
Dependent variable: LNGI				
D(CNE)	0	0	0.110969	0.9118
D(D(CNW))	0	0	0.012388	0.9901
CointEq(−1)	−0.983164	0.091917	−10.6962	0
Dependent variable: SNG				
D(CNE)	0	0	−0.73723	0.4625
D(D(CNW))	0	0	0.835434	0.4052
CointEq(−1)	−0.873453	0.089253	−9.78628	0
Dependent variable: TEL				
D(CNE)	0	0	1.383263	0.1693
D(CNE(−1))	0	0	0.101994	0.9189
D(CNE(−2))	0	0	2.33551	0.0213
D(D(CNW))	0	0	0.221264	0.8253
CointEq(−1)	−1.005732	0.091574	−10.9827	0
Dependent variable: TGN				
D(CNE)	0	0	2.840856	0.0053
D(CNE(−1))	0	0	3.286466	0.0013
D(D(CNW))	0	0	−2.36328	0.0198
CointEq(−1)	−1.086295	0.088083	−12.3326	0

Source: author's own work. Notes: for the definition of variables, please see Table 2.

4.2.4. Variance Decomposition Research. To determine the extent to which COVID-19 variables contribute to the explanation of energy market variables, the variance decomposition approach was used, the outcomes being revealed in Table 12. Decomposition variation indicates the extent to which a certain variable can explain the evolution of the variation of another variable. In addition, it shows which of the independent variables is stronger in explaining the variability of dependent variables over time.

From the results obtained after the decomposition of the variance, it can be noticed that the number of new cases of COVID-19 registered in Europe shows a higher contribution in the case of EEX-B, EEX-P, LNGI, EL, SNG, and TGN, whereas for the variables BET-NG, APX, TEL, the largest

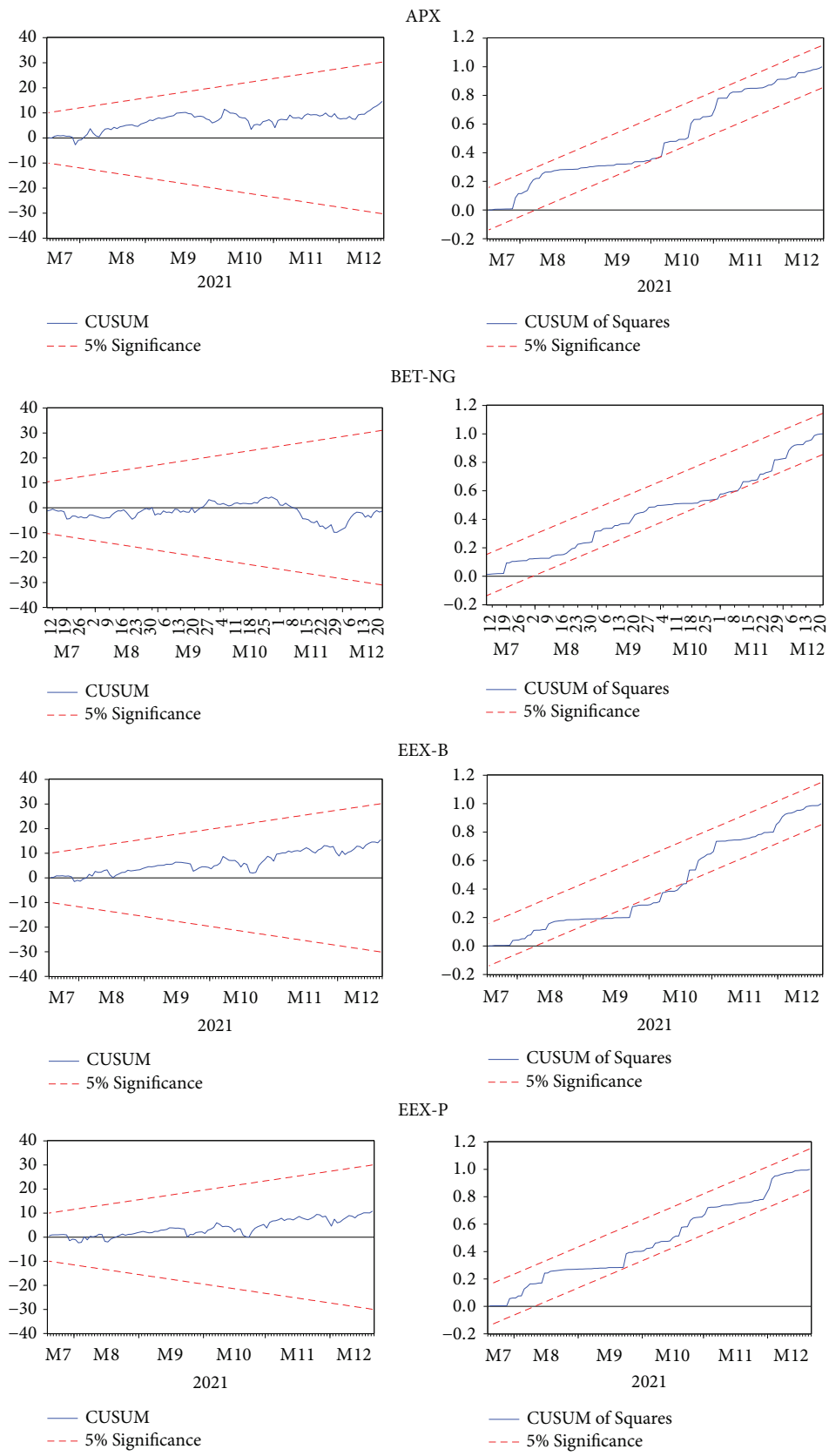

Figure 9: Continued.

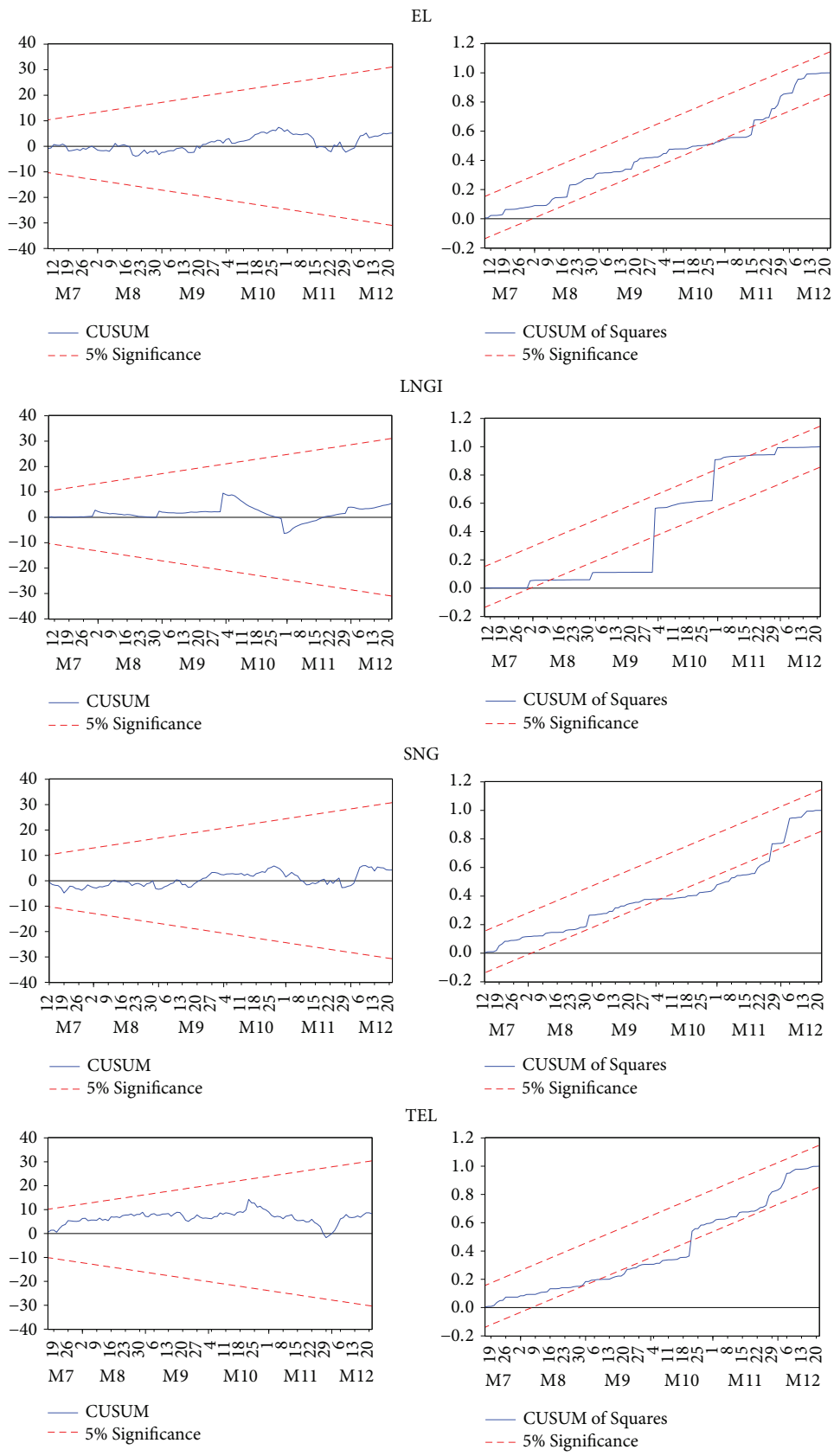

Figure 9: Continued.

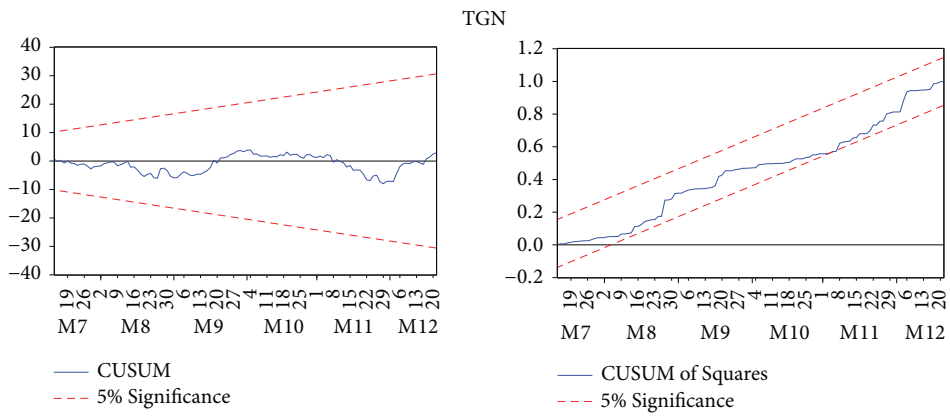

Figure 9: CUSUM test and CUSUM of square test of each ARDL model. Source: author's own work. Notes: for the definition of variables, please see Table 2.

Table 11: ARDL diagnosis tests.

	APX		
	Breusch–Godfrey serial correlation LM test		
F-statistic	1.956852	Prob. *F*(2, 111)	0.1461
Obs*R-squared	4.086932	Prob. Chi-square(2)	0.1296
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	0.871964	Prob. *F*(6, 113)	0.5179
Obs*R-squared	5.310026	Prob. Chi-square(6)	0.5047
Scaled explained SS	13.70353	Prob. Chi-square(6)	0.0331
	BET-NG		
	Breusch–Godfrey serial correlation LM test		
F-statistic	0.095708	Prob. *F*(2, 117)	0.9088
Obs*R-squared	0.200903	Prob. Chi-square(2)	0.9044
	Heteroskedasticity test: Breusch-Pagan-Godfrey		
F-statistic	2.362356	Prob. *F*(3, 119)	0.0747
Obs*R-squared	6.91355	Prob. Chi-square(3)	0.0747
Scaled explained SS	10.20941	Prob. Chi-square(3)	0.0169
	EEX-B		
	Breusch–Godfrey serial correlation LM test		
F-statistic	1.43912	Prob. *F*(2, 110)	0.2416
Obs*R-squared	3.059835	Prob. Chi-square(2)	0.2166
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	3.030858	Prob. *F*(7, 112)	0.0059
Obs*R-squared	19.11122	Prob. Chi-square(7)	0.0078
Scaled explained SS	36.21409	Prob. Chi-square(7)	0
	EEX-P		
	Breusch–Godfrey serial correlation LM test		
F-statistic	3.67646	Prob. *F*(2, 109)	0.0285
Obs*R-squared	7.583398	Prob. Chi-square(2)	0.0226
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	2.361501	Prob. *F*(8, 111)	0.0219
Obs*R-squared	17.45327	Prob. Chi-square(8)	0.0257
Scaled explained SS	36.76958	Prob. Chi-square(8)	0
	EL		
	Breusch–Godfrey serial correlation LM test		
F-statistic	0.078257	Prob. *F*(2, 117)	0.9248
Obs*R-squared	0.164321	Prob. Chi-square(2)	0.9211
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	1.515814	Prob. *F*(3, 119)	0.214

Table 11: Continued.

	APX		
	Breusch–Godfrey serial correlation LM test		
Obs*R-squared	4.527293	Prob. Chi-square(3)	0.2099
Scaled explained SS	8.60173	Prob. Chi-square(3)	0.0351
	LNGI		
	Breusch–Godfrey serial correlation LM test		
F-statistic	0.03895	Prob. F(2, 117)	0.9618
Obs*R-squared	0.081841	Prob. Chi-square(2)	0.9599
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	0.019132	Prob. F(3, 119)	0.9964
Obs*R-squared	0.059298	Prob. Chi-square(3)	0.9962
Scaled explained SS	1.165012	Prob. Chi-square(3)	0.7614
	SNG		
	Breusch–Godfrey serial correlation LM test		
F-statistic	0.210536	Prob. F(2, 115)	0.8105
Obs*R-squared	0.445074	Prob. Chi-square(2)	0.8005
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	4.599008	Prob. F(4, 117)	0.0017
Obs*R-squared	16.57594	Prob. Chi-square(4)	0.0023
Scaled explained SS	38.89259	Prob. Chi-square(4)	0
	TEL		
	Breusch–Godfrey serial correlation LM test		
F-statistic	0.4525	Prob. F(2, 112)	0.6372
Obs*R-squared	0.969886	Prob. Chi-square(2)	0.6157
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	0.837925	Prob. F(6, 114)	0.5431
Obs*R-squared	5.110863	Prob. Chi-square(6)	0.5297
Scaled explained SS	14.91187	Prob. Chi-square(6)	0.021
	TGN		
	Breusch–Godfrey serial correlation LM test		
F-statistic	0.246637	Prob. F(2, 114)	0.7818
Obs*R-squared	0.525616	Prob. Chi-square(2)	0.7689
	Heteroskedasticity test: Breusch–Pagan-Godfrey		
F-statistic	1.580195	Prob. F(5, 116)	0.1711
Obs*R-squared	7.779751	Prob. Chi-square(5)	0.1688
Scaled explained SS	10.33263	Prob. Chi-square(5)	0.0663

Source: author's own work. Notes: for the definition of variables, please see Table 2.

contribution comes from the number of new COVID-19 cases registered globally.

4.2.5. Causality Assessment. To explore causality between selected variables, the Granger causality test is applied. To employ the Granger causality test, the data series must be stationary and have therefore been converted into stationary series. Table 13 shows the results after the Granger causality test for the energy market and COVID-19 variables.

The causality test confirms that between the number of new cases of COVID-19 registered in Europe and TEL, respectively TGN, there is a one-way relationship running from CNE to both energy companies listed on the BSE. From an econometric point of view, we came to this decision because the p-value is below the threshold of 10% and 5% respectively, which leads to the rejection of the null hypothesis: the number of new cases of COVID-19 in Europe does not determine Granger-type causation variables analyzed.

To our knowledge, the existing studies on the impact of COVID-19 on the energy market during July-December 2021, did not address this type of relationship study, the novelty of the article deepening consisting in this ARDL model that will allow the analysis of long-term relationships between variables selected, as well as the decomposition of the variance and the identification of the causal relations.

The innovations of this research include the following aspects. First, this study measured the impact of the COVID-19 pandemic on the energy market. Second, this research integrated advanced econometric models to obtain detailed results on the long-term or short-term relationships between COVID-19 variables and the energy market. Third, this study will help fill the gap in the literature and will be a focal point for future energy market research during the COVID-19 pandemic.

Table 12: The results of the variance decomposition.

Variance decomposition of BET-NG			
Period	BET-NG	CNE	D(CNW)
4	98.29786	0.515906	1.186235
Variance decomposition of APX			
Period	APX	CNE	D(CNW)
4	95.79962	0.579511	3.620871
Variance decomposition of EEX-B			
Period	EEX-B	CNE	D(CNW)
4	98.26753	1.351639	0.380828
Variance decomposition of EEX-P			
Period	EEX-P	CNE	D(CNW)
4	97.44553	1.829981	0.724489
Variance decomposition of LNGI			
Period	LNGI	CNE	D(CNW)
4	97.0762	2.171236	0.75256
Variance decomposition of EL			
Period	EL	CNE	D(CNW)
4	97.45433	1.630974	0.914701
Variance decomposition of SNG			
Period	SNG	CNE	D(CNW)
4	96.26766	2.22723	1.505114
Variance decomposition of TEL			
Period	TEL	CNE	D(CNW)
4	98.29561	0.720873	0.983517
Variance decomposition of TGN			
Period	TGN	CNE	D(CNW)
4	91.5325	5.388915	3.078584

Source: author's own work. Notes: null hypothesis: no long-run relationships exist. Notes: for the definition of variables, please see Table 2.

5. Concluding Remarks and Policy Implications

The extreme insecurity of the pandemic and the related economic failures have made markets very volatile and unpredictable. Hence, the risks of the global financial market boosted considerably in response to the disease. In this article, we examined how the number of new COVID-19 cases in Europe and globally is affecting the Romanian energy market. To achieve our goal, we used daily data for the period July 1, 2021–December 21, 2021, which includes the fourth wave of the COVID-19 pandemic. We have selected a wide range of variables that characterize the energy market: energy price indices, natural gas, and the BET-NG index of the Bucharest Stock Exchange. Also, we covered several companies listed on BSE that act in the energy field which are also among the most traded companies in Romania.

Due to the mix of stationary and nonstationary variables, the ARDL model was adopted in this research. Through this model, it was feasible to study the relationships that are established in the long and short term. There should be noted that the number of short-term relationships was higher, which is also due to the short episodes of high volatility recorded in the investigated timeframe. However, in the long run, there is a positive impact on the number of new cases in Europe and in the world on the return of TGN. In contrast, no long-term relationship was identified between COVID-19 variables and the price of electricity and natural gas. In the short term, a negative impact of new cases of COVID-19 infection in Europe on the price of electricity has been identified. As well, in the short run, the positive impact of the new COVID-19 cases is noticed in the companies traded on BSE. Hence, an increase in the number of new COVID-19 cases in Europe during the analyzed period leads to a rise in the share price of TEL. In the same vein, an increase in the number of new cases of COVID-19 both in Europe and globally have a positive impact on the price of TGN shares.

To explore causality between variables, the Granger causality test was applied. One-way causal relationships have been identified from the number of new COVID-19 cases in Europe to the returns of TEL and TGN. Nevertheless, no Granger causal relationships have been found between the COVID-19 variables and the price of electricity or natural gas.

This research showed that the variables do not have a direct impact on energy prices, but certainly, the effects of the COVID-19 pandemic are those that contributed to the increase in energy prices, obviously indirectly by reflecting the negative effects of measures to combat the spread of COVID-19 virus. Our empirical findings provide insight into how the energy market is affected by the COVID-19 pandemic.

As it turned out, prices have risen, and this is due to the supply deficit. Therefore, we consider a series of measures that should be implemented by the administrative sector in

Table 13: Results of granger causality test.

Null hypothesis	*F*-statistic	Prob.
D(D(CNW)) does not granger cause D(CNE)	0.71527	0.6381
D(CNE) does not granger cause D(D(CNW))	1.3473	0.2432
APX does not granger cause D(CNE)	1.048	0.3989
D(CNE) does not granger cause APX	0.55642	0.764
BET-NG does not granger cause D(CNE)	1.01343	0.4207
D(CNE) does not granger cause BET-NG	1.56439	0.1649
EEX-P does not granger cause D(CNE)	1.56161	0.1658
D(CNE) does not granger cause EEX-P	1.45446	0.2012
EEX-B does not granger cause D(CNE)	1.85628	0.0954
D(CNE) does not granger cause EEX-B	1.26117	0.2818
EL does not granger cause D(CNE)	1.02095	0.4159
D(CNE) does not granger cause EL	0.85816	0.5284
SNG does not granger cause D(CNE)	1.02123	0.4157
D(CNE) does not granger cause SNG	1.19495	0.3149
TEL does not granger cause D(CNE)	0.86893	0.5204
D(CNE) does not granger cause TEL	**1.99231**	**0.0733**
TGN does not granger cause D(CNE)	1.21391	0.3051
D(CNE) does not granger cause TGN	**3.89549**	**0.0015**
APX does not granger cause D(D(CNW))	0.35365	0.9063
D(D(CNW)) does not granger cause APX	0.12934	0.9924
BET-NG does not granger cause D(D(CNW))	1.94886	0.0799
D(D(CNW)) does not granger cause BET-NG	1.76113	0.1144
EEX-P does not granger cause D(D(CNW))	0.43535	0.8537
D(D(CNW)) does not granger cause EEX-P	0.66365	0.6791
EEX-B does not granger cause D(D(CNW))	0.3282	0.9208
D(D(CNW)) does not granger cause EEX-B	0.48702	0.8167
EL does not granger cause D(D(CNW))	0.58454	0.7419
D(D(CNW)) does not granger cause EL	0.4387	0.8514
SNG does not granger cause D(D(CNW))	1.8463	0.0973
D(D(CNW)) does not granger cause SNG	1.71958	0.1238
TEL does not granger cause D(D(CNW))	1.93276	0.0824
D(D(CNW)) does not granger cause TEL	0.96973	0.4496
TGN does not granger cause D(D(CNW))	0.76793	0.5968
D(D(CNW)) does not granger cause TGN	1.76057	0.1146

Source: author's own work. Notes: sample: 7/01/2021–12/21/2021. For the definition of variables, please see Table 2.

order to avoid a social crisis. In the immediate vicinity, aid may be provided to vulnerable household consumers for price increases, either in cash or by partial payment of the budget bill; temporary delays in paying bills and avoiding disconnections during this period; reduction of taxes and duties (for the most vulnerable consumers); state aid to industry; increasing market liquidity and transparency; and investigations into speculation or market abuse.

We also presume that increasing investment in renewables, as well as energy efficiency in buildings and industry, is a solution that will only bring positive results in the long run. As a result, transitioning to clean energy is the best way to protect against future price shocks and should be accelerated. Therefore, the findings of this study can help investors optimize their portfolios while also providing guidance to decision-makers and regulators. In addition, in order to help the oil market, governments may relax quarantine restrictions and reopen their businesses [12].

Because of the ongoing changes in the pandemic, as well as the various geopolitical and economic events that may occur, more research on this topic is likely in the future. These findings should be considered by investors and policymakers because they argue that the relationship between energy goods and COVID-19 is dynamic rather than linear. For the reason that the current study is limited to the fourth wave of the disease, upcoming investigations should also cover the preceding COVID-19 waves. The current study is limited to merely the Romanian energy market and the fourth wave of the COVID-19 pandemic. However, further research avenues should cover more international energy markets, as well as the prior pandemic period. As well, upcoming studies might assess the co-movements of the energy market with other variables such as gold or agricultural commodities.

Data Availability

Data are available from the authors upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Multivariate Analysis for Overcoming Complexities of Corporate Governance and Managerial Dilemma Using Data Mining Techniques

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The increased number of corporate dirty pools raised serious concerns about the interest of the shareholders. The board room politics, conflict of interest, and bully pulpit proclivity gave birth to the "agency complexities." The complexities of the corporate world made a buzz for the serious thoughts on corporate governance. This analysis aims at an objective and scientific inquiry about the relationship between corporate governance complexities and firm performance by utilizing data mining tools. It aims at overcoming the corporate dilemma over profitability vs. good governance and presenting a scientific model to eradicate the complexities in the corporate governance system and aims at providing a scientific basis to overcome the complex issues of governance faced by the corporate. The multivariate analysis in this paper utilizes a data mining tool for regression analysis and ANOVA. This paper also proposes a mathematical model that supports the study outcomes. The investigation outcomes are not only backed by the mathematical model and scientific tools but also by a comprehensive comparative analysis. The outcome of the investigation clearly mentions the significance and the primacy of each variable in the corporate decisions making process, which will facilitate the organizations in framing their corporate governance policies and will also be helpful to the managers in overcoming the corporate dilemma faced by them.

1. Introduction

The advent of a new era of science, technology, and information revolution paved the way for several structural and regulatory reforms around the world. The great journey of trade and commerce from barter to sole trader and to the gigantic multinational corporations is like a metamorphic transformation of a caterpillar into a beautiful butterfly. This transition played a pivotal role in the genesis of the complex organizational structures which further led to operational framework failures, frauds, and unethical business practices. The increased number of corporate dirty pools raised serious concern about the interest of the investors. "Corporate dirty pools" is a comprehensive term used for insider trading, tunneling, and window dressing. It includes intentional implementation of a lame corporate governance framework, poor risk mitigation policies, fraudulent accounting practices, and fabricated financial reporting.

Accountability, truth and fairness, responsibility, transparency, and disclosure are some of the founding principles of corporate governance. Adherence to higher standards of corporate governance standards involves a cost to the organization. Harvard law school forum on corporate governance, in their report on global and regional trends in corporate governance for the year 2022 has mentioned the climate change and increased demands of assertive investors for sustainable ways of doing business (Fields et al.). Implementing the provisions related to financial reporting and disclosures on sustainability efforts of management for tackling the climate change challenges and simultaneously

fixing the responsibility and accountability of directors and executives for the climate risk oversight are some of the biggest contemporary challenges of corporate governance. Many regulations and standards in this context have already been merged into the International Sustainability Standards Board (ISSB) under IFRS. The pressure for decarbonizing the globe is higher than ever before in the corporate sector. The decision of complying with sustainability standards impacts the profitability of a company negatively, as it is a "costly affair" for any organization. The poor financial performance of the company questions the efficiency and effectiveness of management. This is one of the typical cases of an ethical dilemma for the managers in which they have to choose between good corporate governance that advocates environmental sustainability or profitability.

The board room politics, conflict of interest, and bully pulpit proclivity gave birth to the "agency problems." The term "bully pulpit proclivity" refers to the management's unethical acts. It includes running a self-inclined agenda at the cost of investors' interest and misusing their powerful positions for whitewashing their acts in the public domain. All these collectively increased the complexities of corporate governance and gave a buzz to serious thoughts on the issue. Though the stringent laws and regulative framework endeavors investors protection, but in the recent past a number of corporate swindles unnerved the measures taken by the government to strengthen corporate governance. An abysmal downfall of corporate ethics and morality alarmed the world to rethink this complex governance issue and come up with a better and stronger governance mechanism.

This corporate pandemonium drew the attention of many researchers and academicians around the globe. The archive is flooded with various empirical and descriptive studies on this complex matter. Each investigation has its own pattern and different outcomes. There are some studies that reveal a positively significant relationship between corporate governance and firm performance; some studies reveal a negative and insignificant relationship; and a few studies even show the mixed result.

This study attempts at providing new dimensions to the investigation by focusing on the complexity of corporate governance issues. The relationships between the organizations and their stakeholders in general and the stockholders are highly complex in nature (Georgian et al.). The majority of the previous studies are based on two or maximum up to three corporate governance elements whereas, we have taken six independent variables as the components of corporate governance. Our study aims at an objective and scientific inquiry about the relationship between the complexities of corporate governance and firm performance. In this multivariate analysis, we have utilized various data mining tools such as SPSS, regression analysis, and ANOVA. We have also proposed a mathematical model which supports the study outcomes. The investigation outcomes are not only backed by the mathematical model and scientific tools but also by a comprehensive comparative analysis. For our investigation purpose the board composition (BO), ownership structure (OW), board remuneration (BOR), board and shareholders meetings (BM), transparency and shareholders rights (TSR), and corporate governance policies of the firm (CGCP) are primarily taken as corporate governance components for measuring financial performance accounting-based parameter, i.e., return on capital employed (ROCE) is used. The study is based on the 121 small caps, mid-cap, and large-cap companies listed on the Bombay stock exchange (BSE). The data are collected through the Prowess database. The key contribution of the paper are as:

(i) The study aims at providing a scientific basis to overcome the complex issues of governance faced by the corporate.

(ii) We have applied a combination of data mining tools such as Support Vector Machine (SVM) with the help of Hyperplane. Data mining tools along with mathematical modeling make our methodology robust and study outcomes more rational and scientific.

(iii) We have applied a multidimensional approach by focusing on key corporate governance variables in a single study.

(iv) The outcome of the investigation clearly mentions the significance and the primacy of each variable in the corporate decisions making process, which will facilitate the organizations in framing their corporate governance policies and will also be helpful to the managers in overcoming the corporate dilemma faced by them.

2. Related Work

In the past decade, many researchers investigated corporate governance from various paradigms but failed to reach a common stand on governance and profitability association. Many authors discussed the complexities of modern organizational structures and the dynamics of corporate governance. The study outcomes differed with the change in the methodology, size of the company, and the governance framework of the countries. Some results advocated positive association, some revealed negative and nonsignificant associations and there are some which showed mixed results [1]. Manson and Zaman [2] also questioned the legitimacy of the controllers who are at the helm of affairs and yet only want to reap the benefits without being held responsible for their deeds. Another study by [3]; Kim and Lee [4] show that corporate governance has a strong positive impact on the firm's performance. The study revolves around the East Asian financial crisis period, i.e., in the year 1997-98, that further glorifies the independent directors' traditional role of improving and monitoring management.

Dwivedi and Jain [5] in their empirical analysis for the time-period of 1997–2001 on 340 Indian companies revealed a positive and significant association between corporate governance and firm performance. Board size and ownership were taken as the variables for corporate governance and firm performance was evaluated using Tobin Q. Similarly in another study based on Indian companies

Gupta [6] investigated the level of adherence to corporate governance norms in selected automobile companies and found that those automobile companies' policies and practices were in line with the regulatory framework of corporate governance in the country.

Monks and Minow [7] in their book titled corporate governance attempts to explain the significance of the practical applicability of corporate governance by using various real-life corporate examples. A study based on Iranian companies listed on Tehran stock exchange for the two consecutive financial years 2005 and 2006 by Mashayekhi and Bazaz [8] on the same issue by utilizing the regression analysis revealed that a larger board size will affect the performance of the company. They also strongly advocated the role of independent directors in improving the firms' financial out-turn.

Wang et al. [9] in their study based on 106 High techs, medium, and small-size Chinese firms found a positive relationship between ownership concentration and corporate performance. They also proved that the firms which have a greater number of board meetings take better decisions and they perform well. Furthermore, they state that there is a direct relationship between the board remuneration and corporate performance, i.e., the companies, which pay their director's good remuneration, perform better in terms of financial efficiency.

On the other hand, there are some studies that outrightly reject the premise of any type of significant association between good governance of corporate and firm financial efficiency. Some studies reveal a weak or insignificant relationship between corporate governance and the firm's performance. Bhagat et al.[10] in their study found no correlation between board independence and long-term firm performance. Similarly, another study by Bauer et al. [11] on European firms found a negative association between governance standards for corporate and the performance of the firms.

By using generalized linear model (GLM) Fauzi and Locke [12] proposed that the board, Board committees, managerial ownership, and block holding ownership have a positive influence on the firms' performance in New Zealand. The study results based on 79 firms in New Zealand were indicative of poor firm performance due to block holding ownership patterns and nonexecutive director's excessive interference.

Vo and Phan [13] in their research investigation based on Vietnamese firms found that Board compensation is positively associated with firm performance whereas Board size has a negative relationship with firm performance. It further advocated that there is no link between independent directors and a firm's performance. It shows a nonlinear relationship between ownership and corporate governance. The study utilized feasible generalized least square (FGLS) regression. Board size, board independence, and board remuneration were a parameter for corporate governance whereas the return on assets (ROA) was taken as representative of a firm's performance.

Moscu [14] In their investigation based on Romanian companies utilized debt-equity ratio as the firm efficiency yardstick and board characteristics as corporate governance parameters and utilized regression analysis to investigate the relationship between them. Their research outcome revealed a direct relationship between board sizes and firm performance. It implies that the larger the board size better is the firm's output. On the other side nonexecutive directors (NED) and firm performance were found negatively associated. On similar lines, in a study on the firms in the life science sector in Canada, Cook [15] propounded that nonexecutive directors have minimal influence on a firm's efficiency.

Kim and Kim [16] in their study on governance social responsibility and credit rating found that corporate social responsibility and corporate governance have a positive impact on the firm's credit rating. Higher the corporate social responsibility and corporate governance scores better is the credit rating of the firm and vice versa. Another study on a similar line found a direct association between corporate governance and firm performance, Jaser and Quasim [17] applied regression analysis on 281 firms listed on Abu Dhabi stock exchange (UAE). They have used return on assets (ROA) and Tobin Q as the parameters for the firm's performance.

Kandukuri et al. [18] in their study on Indian companies found similar results. The study results revealed the imbrications of private companies over public companies globally. Al-Gamrh and Ku Ismail[19] in their research investigation found that return on equity and profitability were not associated with the corporate governance variables. But overall corporate governance had a positive influence on the performance of the firm. The study covered 20 companies in the Indian manufacturing sector.

Naimah and Hamidah [20] in their research found that board audit committee meetings and quality of audit were directly related to the profitability of the company, whereas leverage, board independence, and size of the company were indirectly associated with the profitability of the company. The authors utilized regression analysis for the study.

Ilham et al. [21] in their investigation of the Turkish companies found that corporate governance and performance of the firms were positively associated. The study outcomes are suggestive of a significantly positive relationship between ownership concentration and board size. On the other hand, Balagobei [22] in her study based on Sri Lankan firms found smaller board sizes more suitable for better firm performance. The study also found a negative impact of the audit committee on the firm's performance.

A study based on Sri Lankan financial institutions Danoshana and Ravivathani [23] found that the size of the board and audit committee matters. Larger the size of the board and audit committee better the performance of the company but, on the other hand, frequency of the board meetings were found to be indirectly associated with the firm performance. It means that the firms having a greater number of board meetings did not perform financially well. Another study by Bhagat and Bolton [24], which is a sequel of their previous investigation in the year 2008 on corporate governance and firm performance took the data for the period of 2003 to 2016. Based on the long-term analysis the

study results suggested that director stock ownership helped in improving the performance of the firms and helped risk mitigation as well.

Similarly, Bijalwan et al. [25] in their exploratory analysis of corporate governance using supervised data mining tools found that there is a significantly positive relationship between board meetings and firm performance. They found that the firms with a greater number of board meetings performed better as compared to the firms with a lower number of board meetings. The study outcomes further showed that the remuneration paid to directors had no effect on the firm performance.

The recent study based on the firms listed on Abu Dhabi stock exchange (ADX) in the United Arab Emirates (UAE) by Al-Gamrh et al. revealed that more investment opportunities lead to poor firm performance. The study characterized UAE firms with lame corporate governance practices. The study further mentions that stronger corporate governance helps in mitigating the negative impact of investment opportunities. Malhotra et al. [26] on 242 companies listed on Bombay stock exchange (BSE) for the period of 2015 to 2019 that consisted of both public sector and private sector firms found that the public sector firms had a better corporate governance practice as compared to the private sector firms in India.

Fatma and Chouaibi [27] examined the impact of the characteristics of two CS mechanisms, i.e., board of directors and ownership structure. It is based on the firm value of European financial institutions. Salehi et al. [28] aimed to measure the relationship between corporate sectors and managerial entrenchment in companies listed on Tehran stock exchange. They used panel data regression to test the hypothesis. Almaleki et al. [29] aimed to investigate the comparability between the impact of managerial pride and overconfidence on financial statements. Velte [30] showed the link between corporate governance and corporate financial misconduct. Guluma [31] aimed to investigate the impact of CG that measures on firm performance and the role of managerial behavior in the relationship between CG mechanism and firm performance. This analysis was based on Chinese listed firms.

Li and Nguyen [32] focused on small and medium-sized enterprises in emerging economies. Their study aimed at the impact of CG on firm value by exploring the mediation mechanism of CSR and organizational identification aligned with CG and firm value. Almaleki et al. [33] aimed to seek the potential impact of board member's characteristics, the level of the firm's CSR. They found from their study that in Iran innovation is willing to be transmitted into firms by industry sources though, In Iraq regardless of the industry index, a positive association between interlocked bounds and firm innovation is established. Their analysis also depicts that board interlock is not considered a mechanism to transmit information about CSR.

There have been many studies in the past covering corporate governance issues from various dimensions which applied either market-based or accounting-based parameters on standard governance key components. Most of the studies utilized two or maximum up to three variables with the standard statistical tools to investigate the nature and degree of relationship among governance variables. Our study is based on the six key components of corporate governance such as board composition (BO), ownership structure (OW), board meeting (BM), board remuneration (BOR), corporate governance codes and policies (CGCP), transparency, disclosure, and shareholders rights (TSR). In this study, corporate governance variables are independent variables, whereas the return on capital employed is used as a dependent variable for determining the financial efficacy of the firm.

After an intense analysis of the literature on the subject, finally, the null hypothesis was developed, whose validity was subjected to a robust scientific investigation.

H0: There is no significant relationship between corporate governance complexity variables and the firm's financial efficacy.

3. Study Design

3.1. Variable Selection and Model Construction. The study uses corporate governance complexity as the independent variable which is made up of six different components viz. board composition (BO), ownership structure (OW), board meeting (BM), board remuneration (BOR), corporate governance codes and policies (CGCP), transparency, disclosure, and shareholders rights (TSR). Whereas firm's performance is a dependent variable which is denoted by return on capital employed (ROCE). Some other factors such as size of the firm (TA), Leverage (LEV), Liquidity (COR) of the firm, and Inventory turnover (IR) are taken as control variables for the study.

3.1.1. Independent Variables. The description of key components of the corporate governance complexity used as an independent variable is described in table no 1. Table 1 includes an explanation of the independent variables, their indicators, description thereof, and the symbolic representation for the validation through a mathematical model.

3.1.2. Dependent Variable. Firm's financial efficacy is the dependent variable for the study. In the previous studies on corporate governance, the financial efficacy of the firm was majorly assessed via market-based measures or accounting-based parameters. This study utilizes the accounting-based ratio, i.e., return on capital employed (ROCE) as a yardstick to measure the financial efficacy of the firm. ROCE is a financial ratio that can be expressed as earnings before interest and tax/capital employed. An ideal ROCE is one, that is, greater than the cost of borrowings of the firm.

3.1.3. Control Variables. Sizes of the firm, leverage, liquidity condition, and inventory ratio are taken as the control variables for the study. Size of the firm is measured according to the total assets held by the company; leverage condition is determined by the debt-equity ratio. For assessment of the liquidity condition of the company, liquidity

Table 1: Independent variables.

Sr.no.	Factors	Indicators	Description	Symbolic
1	Board composition (BC)	(a) board size (b) board independence	(a) total no. of BOD sitting on board (b) ratios of DIRs to ID and ED to NED etc	x
2.	Ownership structure (OS)	Ownership structure	Percentages of shares held by various stake holders in the company	u
3.	Board meetings and share holders' meetings (BSM)	(a) board meetings (b) shareholders meetings	(a) Total no. of board meetings held during the year (b) Total no. of shareholders meetings held during the year. (including provisional meetings)	v
4.	Board remunerations (BR)	Board remunerations	Remuneration paid to the top 3 executives in their natural algorithm	w
5.	Corporate governance codes and practices (CGP)	Corporate governance codes and initiatives	Corporate governance codes and initiatives are taken by the company	z
6.	Transparency and shareholders rights (TSH)	(a) Transparency and disclosure (b) Shareholders rights.	(a) transparency and disclosure norms followed by the company. (b) right to shareholders	t

Table 2: Control variables.

SN	Control variables	Explanation	Symbol
1	Size of firm	Total assets	TA
2	Leverage	Debt/equity	LEV
3	Liquidity	Current assets/current liabilities	COR
4	Inventory turnover	Cost of goods sold/average inventory	IR

ratios are utilized and Inventory turnover is measured with the help of inventory turnover ratio. Table 2 shows control variables utilized for the study.

3.1.4. Model Development. For making the methodology more robust we have proposed two different models. First model is a conceptual support vector machine (SVM) mathematical model which fits a hyperplane for testing the research outcomes as mentioned in below equation:

$$y = a + bx + cu + dv + kw + fz + gt, \tag{1}$$

where x, u, v, w, z, and t are independent variables as explained in the Table 1 and y is dependent variable. The second is an OLS regression model which investigates the relationship between corporate governance and firm's efficacy and is explained with the help of belowmentioned equation:

$$\begin{aligned} \text{ROCE} = {} & \beta 0 + \beta 1BZ + \beta 2BO + \beta 3OW \\ & + \beta 4BM + \beta 5BOR + \beta 6TSR + \beta 7CGCP + \varepsilon, \end{aligned} \tag{2}$$

where the Board size (BZ), Board composition (BO), Ownership structure (OW), Number of Board and shareholders meetings (BM), Board remuneration (BOR), Transparency and shareholders' rights (TSR), and corporate governance Codes and policies (CGCP) are the independent variables. In the equation Return on capital employed (ROCE) is the dependent variable. $\beta 0$ is constant and $\beta 1$, $\beta 2$, $\beta 3$, ... are regression coefficients.

3.1.5. Sampling. The dataset for study is derived from the Bombay stock exchange. The sample consisted of 121 companies, which are inclusive of the companies from all the brackets of corporate for the period of 2015 to 2020. For maintaining the comprehensiveness of the sample stratified random sampling technique was utilized and the sample size was determined by using Cohen's formulae, i.e.:

$$\text{Cohen's d} = \frac{(M_2 - M_1)}{SD_{\text{pooled}}}, \tag{3}$$

where $SD_{\text{pooled}} = \left(\sqrt{(SD_1^2 + SD_2^2)/2} \right)$.

3.1.6. Measurement of Corporate Governance Scores (CGSs). The corporate governance scores are measured by using a structured questionnaire consisting of 51 questions. The questions strictly adhere to the international benchmarks set for good corporate governance. The scorecard based on governance, management, accountability metrics, and analysis (GAMMA) was used for the corporate governance scores (CGS) and weights were developed for corporate governance factors (variables) used in the study. Each segment had an independent score for its subcomponent and weights were assigned to each factor.

4. Results and Discussion

First model Support Vector Machine (SVM) requires fitting hyperplane when y is a dependable variable and others are independent variables. In which:

$y = a + bx + cu + dv + kw + fz + gt$where x, u, v, w, z, and t are independent variables and y is dependent variable.

Let us explain the proposed model with the help of hyperplane.

Put

x1, x2, x3, ..., xm for x.

u1, u2, u3, ..., um for u.

v1, v2, v3, . . ., vm for v.

w1, w2, w3, . . ., Wm for w.

z1, z2, z3, . . ., zm for z.

t1, t2, t3, . . ., tm for g.

$y2$, $y'3$, $y'4$, $y'5$ . . . . . $y'6 = a + bx6 + cu6 + dv\,6 + kw6 + fz6 + gt6$where $y'1$, $y'2$, $y'3$, $y'4$, $y'5$ and $y'6$ are expected values of y with reference to.

$(x1, u1, v1, w1, z1, t1)$, $(x2, u2, v2, w2, z2, t2)$ . . . . . $(x6, u6, v6, w6, z6, t6)$

The values y1, y2, . . ., ym are called observed values of y corresponding to x, u, v, wz, and t. The expected values are different from the observed values. The difference $yr - y'r$ for different values of x, u, v, w, z, and t are called residuals.

$$\sum_{1}^{6} (y - y')^2. \tag{4}$$

By introducing a new quantity U, which is the sum of squares of residuals from 1 to 6.

$$U = \sum_{1}^{6} (y_r - y_r')^2 = \sum_{1}^{6} [y_r - (a + bx_r + cu_r + dv_r + kw_r + fz_r + gt_r)]^2. \tag{5}$$

The constants a, b, c, d, k, f, and g are selected in a manner that sum of the squares of the residuals is minimum. After this the proviso for U to be maximum or minimum is as:

$$\frac{\partial U}{\partial a} = \frac{\partial U}{\partial b} = \frac{\partial U}{\partial c} = \frac{\partial U}{\partial d} = \frac{\partial U}{\partial k} = \frac{\partial U}{\partial f} = \frac{\partial U}{\partial g} = 0. \tag{6}$$

By simplifying the ratios, we got If $\partial U/\partial a = 0$, then

$$\sum 2\,(yr - a - bxr - cur - dv\,r - kwr - fzr - gr) = 0, \tag{7}$$

or

$$\sum y = ma + b\sum x + c\sum u + d\sum v + k\sum w + f\sum z + g\sum t \ldots \tag{8}$$

By applying the same logic to

$$\frac{\partial U}{\partial a}, \frac{\partial U}{\partial b}, \frac{\partial U}{\partial c}, \frac{\partial U}{\partial d}, \frac{\partial U}{\partial k}, \frac{\partial U}{\partial f}, \frac{\partial U}{\partial g}. \tag{9}$$

We have derived the Equations (10)–(15).

$$\sum xy = a\sum x + b\sum x2 + c\sum xur + d\sum vx + k\sum wx + f\sum zx + g\sum tx, \tag{10}$$

$$\sum yu = a\sum u + b\sum xu + c\sum u2 + d\sum vu + k\sum wu + f\sum zu + g\sum tu = 0, \tag{11}$$

$$\sum yu = a\sum u + b\sum xu + c\sum u2 + d\sum vu + k\sum wu + f\sum zu + g\sum tu = 0, \tag{12}$$

$$\sum yw = a\sum w + b\sum xw + c\sum uw + d\sum vw + k\sum w2 + f\sum zw + g\sum tw = 0, \tag{13}$$

$$\sum yz = a\sum z + b\sum xz + c\sum uz + d\sum vz + k\sum wz + f\sum z2 + g\sum tz = 0, \tag{14}$$

$$\sum yt = a\sum t + b\sum xt + c\sum ut + d\sum vt + k\sum wt + f\sum zt + g\sum t2 = 0. \tag{15}$$

These would be taken as normal equations and can be solved for a, b, c, d, k, and f.

For a,

$$
\begin{aligned}
& m \sum x \sum u \sum v \sum w \sum z \sum t - \sum y \\
& \sum x2 \sum xu \sum vx \sum wx \sum zx \sum tx - \sum xy \\
& \sum xu \sum u2 \sum vu \sum wu \sum zu \sum tu - \sum yu \\
& \sum xv \sum uv \sum v2 \sum wv \sum zv \sum tv - \sum yv \\
& \sum xw \sum uw \sum vw \sum w2 \sum zw \sum tw - \sum yw \\
& \sum xz \sum uz \sum vz \sum wz \sum z2 \sum tz - \sum yz \\
& \sum xt \sum ut \sum vt \sum wt \sum zt - \sum t2 \sum yt.
\end{aligned} \tag{16}
$$

Same can be applied to b, c, d, k, f, and g.

$$
D = \begin{bmatrix} m & \sum x & \sum u & \sum v & \sum w & \sum z & \sum t \\ \sum x & \sum x^2 & \sum xu & \sum vx & \sum wx & \sum zx & \sum tx \\ \sum u & \sum xu & \sum u^2 & \sum vu & \sum wu & \sum zu & \sum tu \\ \sum v & \sum xv & \sum uv & \sum v^2 & \sum wv & \sum zv & \sum \Sigma tv \\ \sum w & \sum xw & \sum uw & \sum vw & \sum w^2 & \sum zw & \sum tw \\ \sum z & \sum xz & \sum uz & \sum vz & \sum wz & \sum z^2 & \sum tz \\ \sum t & \sum xt & \sum ut & \sum vt & \sum wt & \sum zt & \sum t^2 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ k \\ f \\ g \end{bmatrix}
= \begin{bmatrix} \sum y \\ \sum xy \\ \sum yu \\ \sum yv \\ \sum yw \\ \sum yz \\ \sum yt \end{bmatrix}. \tag{17}
$$

The condition for U to be minimum is $\partial^2 u/\partial a^2 \geq 0$, for the given data.

It reveals that for the existence of a, b, c, d, k, f, and g variables it is a necessary and sufficient condition that a company will survive if cost function, i.e., $D \neq 0$.

Furthermore, in order to accomplish the research objective and to have a robust outcome, the null hypothesis was put to the test to check its validity. Various statistical tests were applied for a scientific and objective conclusion. To investigate the effect of corporate governance on the firm's efficacy, the regression analysis was applied to the dependent variables, i.e., Firm performance and the independent variables as components of corporate governance complexity as mentioned in Table 1. The investigation outputs are revealed as follows.

Table 3 shows the descriptive statistics for every component of independent variable. The mean represents the average value observed and the standard deviation reveals spread of the values and N is the number of firms utilized for study, i.e., sample size and min and max stands for the minimum and maximum usual values.

Table 4 is about Pearson's correlation coefficients of normally distributed data. The table is about the relationship between independent variables, i.e., corporate governance complexity components, and dependent variables, i.e., firm's financial efficacy parameter (Return on capital employed). Upon statistical investigation is observed that the correlation coefficient is 0.8210 between corporate governance codes and practices (CGCP) and transparency and shareholders' rights (TSR), which shows a positive relationship between the two components of independent variables. As the observed value is greater than 0.50 it can be said that the relationship between CGCP and TSR is very strong. Upon further analysis, it is observed that no other values were found to be significant as all of them were less than 0.50. The observed significance level or p value among these two variables also satisfies the condition of being strongly related as observed $p < 0.001$, which is less than 0.05. Hence, it can be strongly said that these two variables as strongly and positively correlated.

Table 5 is about model summary the superscript is about constants, i.e., corporate governance components utilized for the study such as board size, board composition, ownership structure, number of board and shareholders meetings, board remuneration, transparency and shareholders' rights and corporate governance codes and policies and b indicates a dependent variable, i.e., return on capital employed.

It also manifests about R, R square, adjusted R square, and standard error. The observed value of R in the proposed model is 0.822 which is within the boundaries of the regression analysis range, i.e., 0 -to 1. As the observed value of R in the given model is more than 0.5 it shows a very strong and positive relationship between independent variables and dependent variables. Furthermore, the value of R square is also high, i.e., 0.675 which falls within the range of 0 to 1 it suggests the goodness of the model to fit and accommodate the data well. The Adjusted R squared is 0.661 which further consolidates the claims of R Square.

Table 6 shows the ANOVA test results, it reveals the observed value of sum of squares, degree of freedom (Df), and mean squared for regression and residual. In the table regression outcome is shown as 9519.27 and the residual output is 4574.320 which shows both variations accounted and not accounted for the model, respectively. As it is evident that the sum square of regression output is more than the sum square of residual it means the model exhibits a higher level of variation in the dependent variable. This may need a supporting factor to facilitate the account for a higher degree of variation observed in the dependent variable. Furthermore, the observed F value is 47.86, which is derived by dividing regression mean square (1903.854) from residual mean square (39.77). The total number of degrees of freedom is the number of cases minus 1. The significance value of

Table 3: Descriptive statistics.

	N	Mean	Std deviation	Min	Max
ROCE percentage	121	17.88	16.25	−14.62	50.38
Board composition	121	67.27	25.36	16.55	117.99
Ownership structure	121	39.12	4.257	30.62	47.62
Board and shareholders meeting	121	39.21	15.33	8.55	69.87
Board remunerations	121	88.43	24.16	40.11	136.75
Corporate governance codes	121	68.81	19.55	29.71	107.91
Transparency and shareholders' rights	121	77.59	17.58	42.43	112.74

Table 4: Correlation.

		ROCE (%)	Board composition	Ownership structure	Bsm score	Board remunerations	Corporate governance codes	Transparency and shareholders rights
Pearson correlation	ROCE percentage	1.000	0.106	0.095	−0.019	−0.059	0.119	0.116
	Board composition	0.106	1.000	0.183	0.037	0.036	0.150	0.160
	Ownership structure	0.095	0.183	1.000	0.435	−0.005	0.254	0.243
	Board and shareholders meeting	−0.019	0.037	0.435	1.000	0.062	0.148	0.200
	Board remunerations	−0.059	0.036	−0.005	0.062	1.000	0.181	0.137
	Corporate governance codes	0.119	0.150	0.254	0.148	0.181	1.000	0.821
	Transparency and shareholders' rights	0.116	0.160	0.243	0.200	0.137	0.821	1.000
Sig. (1-tailed)	ROCE percentage	0	0.124	0.150	0.420	0.259	0.096	0.103
	Board composition	0.124	0	0.022	0.342	0.346	0.050	0.040
	Ownership structure	0.150	0.022	0	0.000	0.478	0.002	0.004
	Board and shareholders meeting	0.420	0.342	0.000	0	0.248	0.053	0.014
	Board remunerations	0.259	0.346	0.478	0.248	0	0.023	0.067
	Corporate governance codes	0.096	0.050	0.002	0.053	0.023	0	0.000
	Transparency and shareholders' rights	0.103	0.040	0.004	0.014	0.067	0.000	0
N	ROCE percentage	121	121	121	121	121	121	121
	Board composition	121	121	121	121	121	121	121
	Ownership structure	121	121	121	121	121	121	121
	Board and shareholders meeting	121	121	121	121	121	121	121
	Board remunerations	121	121	121	121	121	121	121
	Corporate governance codes	121	121	121	121	121	121	121
	Transparency and shareholders' rights	121	121	121	121	121	121	121

Table 5: Model summary b.

Model	R	R square	Adjusted R square	Standard error	R square change	F change	Df1	Df2
1	0.822	0.675	0.661	6.306	0.675	47.864	6	114

Table 6: ANOVA.

Model	Sum of squares	Df	Mean square	F	Sig.
Regression	9519.27	6	1903.854	47.86	0.000
Residual	4574.320	114	39.77		
Total	14093.592	120			

Table 7: Coefficients.

	Unstandardized coefficients		Standardized coefficients	T	Sig.	Correlations		
	B	Std. error	Beta			Zero-order	Partial	Part
(Constant)	2.255	15.63		0.144	0.886			
Board composition	0.050	0.061	0.078	0.821	0.413	0.106	0.077	0.075
Ownership structure	0.312	0.406	0.082	0.769	0.443	0.095	0.072	0.071
Board and shareholders meeting	−0.077	0.110	−0.073	−0.70	0.483	−0.019	−0.066	−0.06
Board remunerations	−0.052	0.063	−0.077	−0.81	0.415	−0.059	−0.076	−0.07
Corporate governance codes	0.058	0.136	0.069	0.424	0.672	0.119	0.040	0.039
Transparency and shareholders' rights	0.048	0.151	0.052	0.317	0.752	0.116	0.030	0.029

Table 8: Residuals statistics.

	Minimum	Maximum	Mean	Std. deviation	N
Predicted value	7.6527	24.7834	17.8812	3.08994	121
Residual	−2.02594E1	95.80276	0.00000	15.96239	121
Std. predicted value	−3.310	2.234	0.000	1.000	121
Std. residual	−1.237	5.850	0.000	0.975	121

$F \leq 0.001$, which is much lower than the desired less than 0.05 condition.

As it is evident in Table 6, the observed residual value of 4574.320 is less than regression value of 9519.27 and the significant value of $F \leq 0.001$ with this it can be concluded that the components of independent variables have done a good job in explaining the variations in the dependent variable.

Table 7 is about coefficients both standardized and unstandardized. In the given model the dependent variable (return on capital employed) = 0.050 board composition 2.255. Independent variables can be measured in different units. The standardized coefficients = 0.078 or betas try to make coefficients more comparable. The $t = 0.144$, which is less than +2 makes the value of regression more nonsignificant.

Table 8 is about residual statistics that explain the mean and standard deviations of predicted value, residual value, standard predicted value, and standard residual value.

By applying them to proposed OLS Regression model no I, we have derived the belowmentioned regression output for the model.

$$Y = 2.255 + 0.050\,x + 0.312\,u - 0.077\,v - 0.052\,w + 0.058\,z + 0.048\,t \ldots\ldots\ldots\ldots\ldots\ldots 8, \tag{18}$$

where, Y = Return on capital employed x = Board composition u = Organization structure v = Board and Shareholders Meetings w = Board Remuneration z = Corporate governance policies t = Transparency and shareholders rights.

Many researchers have worked on the same issue in line with investigating the relationship between corporate governance and the firm's efficacy using different tools and techniques. Our contributions to the subject matter can differentiate in Table 9.

Table 9: Comparative table.

	Point of difference											
Related work	Neeraj Dwivedi and Arun Kumar Jain (2005)	Gupta (2006)	Zhen Yi Wang, Li Su and Ying Tang (2007)	Sanghoon Lee (2008)	Fauzi, F and Locke, S.C. (2012)	Cook, *R*. (2013)	Vo, *D*. and Phan, T. (2013)	Amare Mohammed Jaser, Quasim (2014)	Rajya Lakshmi Kanduri, Laila Memdani, P. Raja Babu (2015)	Akshita Arora, Chandan Sharma (2016)	Zahroh Naimah and Hamidah (2017)	Bijalwan J.G, Bijalwan. A
ANOVA	X	X	X	X	X	X	X	X	X	X	X	✓
Correlation	X	✓	✓	X	✓	X	X	✓	✓	✓	X	✓
Regression	✓	X	X	✓	X	✓	✓	✓	X	X	✓	✓
Multivariate analysis	X	X	X	✓	✓	X	✓	X	X	X	X	✓
Mathematical model	✓	X	X	✓	✓	X	✓	X	X	X	X	✓
Standard governance scoring scale	X	X	X	X	X	X	X	X	X	X	X	✓
Comprehensiveness of sample	X	X	X	X	X	X	X	X	X	X	X	✓
Positive relations	✓	✓	✓	✓	✓	X	X	✓	✓	✓	✓	✓
Negative relations	X	X	X	X	X	✓	✓	X	X	X	X	✓

5. Conclusion and Future Scope

In order to conclude the investigation, outcomes of both models need to be discussed one by one. In the case of the first proposed model which applies hyper plane reveals that for U to be minimum for the given data as:

$$\frac{\partial^2 u}{\partial a^2} \geq 0. \tag{19}$$

It refers that the existence of a, b, c, d, k, f, and g variables are a necessary and sufficient condition that a company will survive if cost function, i.e., $D \neq 0$.

On the other hand, the second model utilized for study results into regression equation (8) which states that the board composition, corporate governance policies, and transparency have positive and significant relationship with firms' performance which is evident with the respective coefficients 0.050, 0.058 and 0.048. The coefficients of variables Board remuneration and Board meeting are −0052 and −0.077 which shows a negative relationship with firms' performance. Furthermore, it can be said that the variables corporate governance policies and transparency and shareholders' rights are positively and significantly correlated with each other and do have a positive relationship with the firms' performance. A sound ownership structure is indicative of good firm performance on the other hand board and shareholders' meeting and board remuneration show negative coefficients −0.077 and −0.052, respectively, which clearly evident a negative relationship with firms' financial efficacy. Our experimental results showed that the residual value of 4574.320 is less than regression value of 519.27 and the significant value of $F \leq 0.001$ with this it can be concluded that the components of independent variables have done a good job in explaining the variations in the dependent variable.

In the nutshell, it can be said that both the models come to the same conclusion, and it can be strongly said that firms with sound board composition with adequate number of independent directors have a good impact on the firm's financial efficacy. Similarly, companies with good corporate governance policies and transparency in their financing and reporting produce better financial results. A sound organizational structure is a supportive factor in the long run. On the other hand, the company management shall abstain from spending excessive time and funds on board meetings and high perks and payouts to the directors as it is a futile expense and will not guarantee any returns. It can be said that for better financial rewards organizations must pay heed on complex corporate governance elements like board composition, sound governance policies, and transparency in their conduct and in handling the material facts.

"The might is right" approach is futile in the realm of good governance. Therefore, the managers and the directors should work in a positive and constructive frame of mind. They should keep the interest of the organization at the apex level of their priority list. It is quite evident from the outcome of both the models that the complexity of corporate governance and the managerial dilemma of profitability vs. good governance can be overcome by balanced board composition, sound governance policies, and transparency in the organizational conduct. In conclusion it can be said that we have applied the multivariate model to study six independent variables however, the same mathematical model and machine learning approach can be applied for studying the relationship between n numbers of variables in the future [34–37].

Data Availability

The source of the author's framework along with the datasets and analysis during the current study is already publicly available on https://prowessiq.cmie.com/ which is maintained by CMIE. SPSS software was used for processing and classification purposes during the author's research experiment.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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Research Article

A Multistage Stochastic Programming Model with Multiple Objectives for the Optimal Issuance of Corporate Bonds

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Large corporations usually cover their capital and operating expenses by issuing bonds with fixed rates and different maturities. This paper proposes a multistage stochastic programming (MSP) model with multiple objectives to optimize bond issuance by satisfying the three common objectives of corporate managers, as follows: (i) Minimizing expected discounted cost under cash liquidity and financial leverage risk constraints. (ii) Minimizing financial leverage risk under expected discounted cost and cash liquidity risk constraints. (iii) Minimizing cash liquidity risk under expected discounted cost and financial leverage risk constraints. We measure liquidity risk as conditional payment-at-risk ($CPaR$), according to the corporation's financial characteristics. Financial leverage risk is captured by conditional financial leverage-at-risk ($CFLaR$), which we design based on conditional value-at-risk ($CVaR$). Through empirical analysis of a company in China, we explore the efficient frontier curves for the three above objectives and provide the corresponding issuance compositions of an optimal bond portfolio. Our MSP model offers guidance for corporations on achieving a trade-off between cost and risk when issuing corporate bonds.

1. Introduction

The dynamic issuance of bonds provides an optimal supply of funds for corporations' capital and operating expenses under uncertainty. Compared with bank loans, bonds issued in tranches are a more flexible source of funding, which facilitates bond repayment (Sierpińska and Bąk, [1]). The composition of the bond portfolio should be considered when issuing bonds in tranches. Numerous studies have investigated the structure of corporate bond portfolios. Aydin [2] showed empirically that corporations with more growth opportunities tend to have more short-term bonds in their portfolios. Kailan, Richard, and Yilmaz [3] found that corporate asset maturity and liquidity were significantly positively associated with bond maturity and that corporate equity structure had some influence on bond portfolios. Körner [4] discussed the determinants of the bond maturity structure of Czech national corporations and found that the issuance of long-term bonds increased with corporation size, leverage, and asset maturity. Orman and Köksal [5] argued that rationalizing debt maturity can help corporations in developing countries grow rapidly and that macroeconomic environmental factors affect bond maturity. Besides illustrating the importance of bond portfolio structure to corporate management, these studies indicated that bond management should consider the volatility in cash savings and other financial uncertainty indicators that affect a corporation's financial structure and cash liquidity expenditure.

This paper proposes a multistage stochastic programming (MSP) model with multiple objectives to deal with the uncertainty of bond issuance in tranches. The stochastic programming model, the most effective solution to asset management problems, is now a dynamic multistage stochastic programming (MSP) model that combines multiple stages of asset and bond simulation and forecasting. In recent years, the MSP model has been widely used in various fields. It offers a very flexible solution to bond portfolio and liquidity management problems. Bradley and Crane [6] were

the first to propose a multistage model of bond portfolio management. Subsequently, Carino et al. [7] applied the MSP theory to the problem of asset liability management in the insurance industry. Many studies have since used the MSP model to solve asset management problems (see Ziemba and Mulvey, Dupacova et al., Hilli, Koivu, Pennanen, and Ranne, Topaloglou N et al, and so on) [8–13]. Regarding sovereign bond management, MSP specializes in optimizing sovereign bond issuance and finding a trade-off between minimum expected cost and minimum risk (Balibek and Köksalan; Consiglio and Staino; Date et al.,) [14–16]. From the perspective of corporate cases, Davi, Álvaro, and Veiga [17] proposed an MSP model that described the dynamic decision-making process behind the issuance of corporate bonds and explored the average risk trade-off between expected bond servicing costs and the expected value of corporate bankruptcy. However, these studies have focused on using MSP to explore the trade-off between minimum cost and minimum risk. Little effort has been made to explore an MSP model with multiple objectives, such as minimizing costs or risk under the constraints of various objectives.

In the development process of scholars for solving the multiobjective bond portfolio optimization problems, many kinds of algorithms have been explored. The solution method of the multiobjective bond portfolio optimization function often lies in the optimization problem of converting many incomparable objectives into a single objective. Since the end of the twentieth century, some scholars have focused on improving algorithms with the aim of improving the iterative solution methods for various multiobjective bond portfolio functions to promote the diversity and validity of solutions (Nakayama, Sharma et al., Nakayama et al., Pai et al., Lam et al., Wang et al.,) [18–23]. It is worth noting that the widely studied nondominated sorting genetic algorithm II (NSGA-II) can find the corresponding optimal solution in the true Pareto optimal front in most problems, and the convergence and calculation speed are constantly improving (Altiparmak et al., Kalyanmoy Deb, Ali Hojjati et al.) [24–26]. For reference in this paper, García et al. combine factors such as return, risk, and liquidity to measure portfolio performance and use L-R type fuzzy numbers to determine the future return and liquidity of each asset. They considered cardinality constraints and upper and lower bound constraints, and improved the algorithm NSGA-II for solving optimization problems that constrained portfolio expected return, semivariance, and expected liquidity (García et al.,) [27]. The improved algorithm of NSGA-II provides an idea for this paper to obtain the optimal bond issuance portfolio of the MSP model with multiple objectives and provides a probabilistic optimization method idea. We can automatically obtain and guide the optimized search space according to the set threshold and make the algorithm adaptively adjust the search direction.

Considering the multistage multiobjective bond portfolio optimization is the main direction of the current multiobjective bond portfolio optimization evolutionary algorithm. In multiclass combinatorial optimization problems, decision-makers perform multiobjective (Pareto) optimization in multiple stages can explore various reasonable and effective optimal solutions in complex situations, and strive to develop algorithms that minimize the computational burden (Balıbek, Banihashemi, Radulescu et al., Zhou et al., Kim et al.,) [28–32]. Ma et al. considered multiple objectives and complex constraint problems at the same time and explored that most of the current multiobjective optimization problems in complex constraint regions are inefficient and have insufficient convergence. They proposed a multistage evolutionary algorithm with constraints stacked on top of each other, which can be processed in different stages of the multiobjective optimization evolutionary algorithm. This algorithm can search for the optimal solution for the next stage adding new constraints under the optimal solution obtained in the current stage. They also propose a strategy for prioritizing constrained processing based on the impact on the unconstrained Pareto front, which can speed up the convergence of the algorithm (Ma et al) [33]. This paper also seeks the optimal solution for MSP model with multiple objectives under complex constraints, we consider the optimal solution at each stage when formulating the bond issuance strategy, and designing the program code for this article by taking into account the ideas of the above solution algorithm.

In this study, we propose an MSP model with multiple objectives that consider the expected discounted cost, cash liquidity risk, and financial leverage risk. We design a conditional financial leverage-at-risk ($CFLaR$) construct to measure corporate financial leverage risk in extreme cases, inspired by the conditional value-at-risk $CVaR$ risk measurement approach. We also develop a corporate cash liquidity risk measurement construct, conditional payment-at-risk ($CPaR$), that improves on the existing liquidity risk measurement method (Balibek and Köksalan) [14]. Most importantly, we derive efficient frontier curves to explore the following three objectives: (i) minimizing the expected discounted cost under different liquidity and financial leverage risk constraints; (ii) minimizing financial leverage risk under different cost and liquidity risk constraints; and (iii) minimizing liquidity risk under different cost and financial leverage risk constraints.

The remainder of this paper is organized as follows. In Section 2, we define the corporate bond management problem and describe its main features. In Section 3, we describe our MSP model in detail. In Section 4, we provide three objective functions that capture corporate managers' preferences for minimizing costs and risks when issuing bonds. In Section 5, we empirically test our model and examine the effective frontiers of our three objectives. Finally, we summarize our results and suggest future research directions in Section 6.

2. Characteristics of the Corporate Bond Management Strategy Formulation Problem

An effective management strategy for issuing corporate bonds needs to meet the expected financing requirements over a specific period and consider the trade-off between costs and risk (Bradley S P and Crane D B) [6]. Because the

repayment cost of corporate bonds is generally higher than that of bank loans, bond repayment may impose a greater financial burden on a corporation and increase the risk of corporate liquidity in the future.

When managing the issuance of corporate bonds, decision-makers mainly consider the repayment cost of issuing new bonds. Here, "the repayment cost" refers to a bond's principal and the interest at different repayment points in the future. The sum of the discounted value of the principal and interest of a bond is defined as the bond's expected repayment cost (O'Connell and Zeldes) [34]. As multistage repayment costs are distributed over several years, it is necessary to discount the principals and interests of bonds issued on each year as a first step when corporate managers consider formulating a bond issuance management strategy.

A multiobjective corporate bond management strategy is characterized by decision-making under uncertainty. Therefore, the corporation needs to consider the evolution of the coupon rates of newly issued bonds in the future, which is a random process (Kim, Ramaswamy, and Sundaresan) [35]. Corporations usually issue corporate bonds at fair prices, and the coupon rates of new bonds are affected by the forward yields of bonds with the same credit rating and the same maturity in the market. The coupon rates of corporate bonds issued in the future are dynamic; therefore, managers cannot predict the size of interest payments with certainty (Koltsaklis and Dagoumas) [36]. Moreover, corporations cannot be sure about the future circumstances of relevant macroeconomic variables. A degree of uncertainty is associated with the evolution of macroeconomic variables such as interest and deposit rates that drive the cost of borrowing (Were and Wambua) [37]. The outcomes of the decision on bond issuance made are subject to the realization of these variables. Hence, managers must analyze the risks caused by these uncertainties.

To a large extent, the risks faced by a corporation when issuing bonds arise from the uncertain payments of new bonds with different maturity terms. These risks mainly include financial leverage risk and liquidity risk. Financial leverage risk, which causes a corporation's losses to increase exponentially, can be measured by the degree of financial leverage, which is mainly determined by bond interest payments. Liquidity risk is based on cash expenses during a cash liquidity planning horizon, and it increases with the proportion of bonds that mature within the cash liquidity planning horizon (Diamond D W) [38]. Controlling the issuance amount of corporate bonds with different maturities at distinct time points can affect both the financial leverage risk and liquidity risk simultaneously. In most cases, there should be a trade-off between cost and liquidity risk. Reducing liquidity risk may require the issuance of long-term bonds with high costs and the maintenance of an excess cash reserve, both of which incur additional costs for the corporation. Given the cost of bonds and the two kinds of risk driven by the payments of the principals and interests of newly issued bonds, corporations must consider the composition of their bond issuance portfolios, which can be adjusted to manage costs and risks simultaneously (Gilchrist et al) [39].

When formulating corporate bond issuance strategies, decision-makers need to consider constraints on bond issuance. Funds raised in the decision-making stage should be sufficient to repay existing bond on the planning horizon. A corporation needs to maintain a sound cash account to meet its operating cash needs (Jindřichovská I and Körner P) [40]. However, the issuance of bonds by a corporation is subject to restrictions imposed by national laws and policies. In particular, the scale of newly issued bonds cannot be too large (Hurst J. W) [41].

The management strategy behind corporate bond issuance involves multiple interrelated decision-making processes, not one-off decisions. The decisions made should work well together to allow the corporation to issue a portfolio of bonds with different maturities to facilitate adaptation to future changes in macroeconomic conditions (Weill P and Ross J. W) [42]. On the basis of observed and predicted macroeconomic trends, the strategy may need to be adjusted in the future. Corporate bond managers need to consider the impact of future adjustment decisions based on the current market environment as well as the corporation's current financial situation and existing corporate outstanding bonds (Donaldson G) [43].

3. Multistage Stochastic Programming Model with Multiple Objectives

3.1. Model Framework. Based on a scenario tree of macroeconomic factors that affect the discounted costs of bonds and the risks faced by corporations, we propose an MSP model with multiple objectives. As a linear equation, our model specifies a sequence of bond issuance decisions at discrete time points during a multistage stochastic planning horizon. We assume that corporations with strong financing needs set a bond issuance strategy at the initial stage of the multistage stochastic planning horizon, which considers the number of bonds to be issued each year and revise this strategy annually. We start with an existing fixed corporate outstanding bond portfolio and a set of anticipated scenarios regarding the future states of relevant macroeconomic variables, such as interest and deposit rates.

Following research on multistage stochastic planning models (Topaloglou et al [11]; Consiglio and Staino [15]; Shapiro et al [44]), we divide the planning horizon of our model into multiple stages, $t\,(t = 1, 2, 3, \ldots, T)$, where T is the final stage. Considering interest payments and discount rates, the total planning period in our MSP model is T years, and a planning interval is 1 year. The formulation of a bond issuance strategy at the beginning of each year is regarded as a decision node, the scenarios between decision nodes combine to form a sequence of joint realizations for a multistage stochastic planning horizon. These sequences of scenarios are linked at each decision node, and the scenario paths cover the entire planning horizon.

Generally, a scenario tree simulates the evolutionary paths of random variables across different stages of the planning horizon by discretizing their joint probability distributions (Boender G) [45]. Uncertainty is the most prominent feature of the scenario tree, and its importance

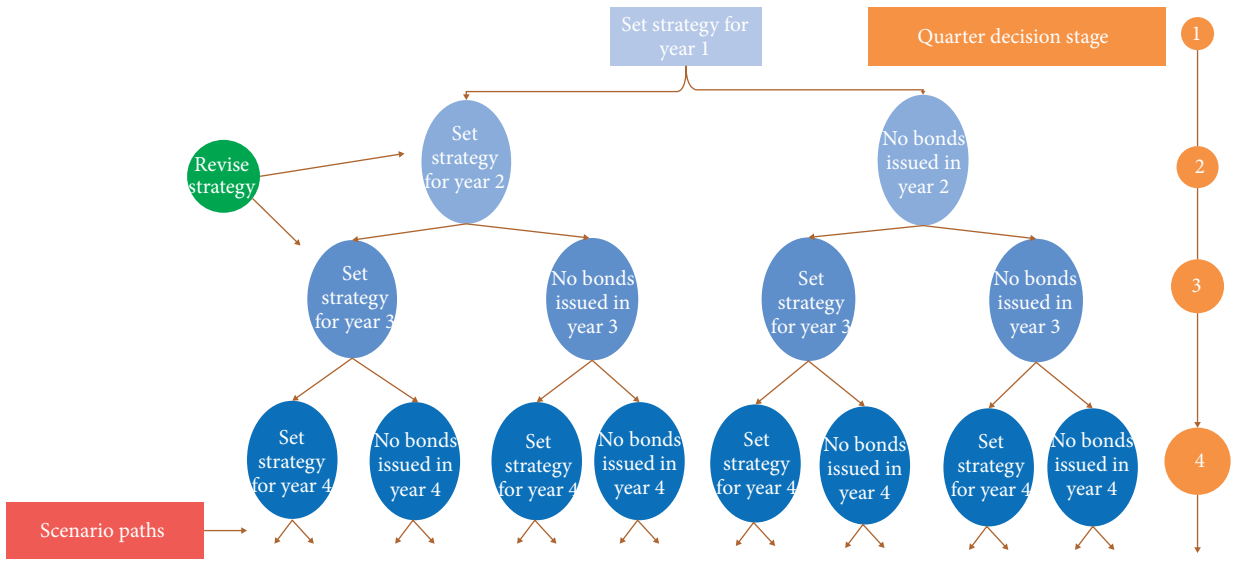


Figure 1: scenario tree of corporate debt issuance strategies.

increases with the number of decision stages. Issuance planning in the first year is affected by the corporation's outstanding bond portfolio, and at the end of the first year, the corporation has a new outstanding bond portfolio and makes a new set of decisions incorporating this new portfolio structure; thus, the updated cash-flow scheme is contingent on the scenario's realization in the first year and the tree branches in the current scenario. Decisions other than the first-stage decision are divided into two categories: issuing a fixed amount of bonds and not issuing bonds. Figure 1 shows a schematic diagram of the paths of the macroeconomic variables in the scenario tree.

As shown in Figure 1, corporations must consider whether to issue bonds at the beginning of each year on the basis of their current financial conditions and the macroeconomic environment after the first year. All discrete joint results are mapped onto the nodes of the scenario tree, i.e., the scenario tree describes a dynamic setting in which a decision is made regarding the future at a given stage. Once the decision is implemented, the information related to the issuance of new corporate bonds is revealed in the following period, and the associated process is repeated.

3.2. Definitions. To prepare a complete formal statement of the model, we first define the parameters and index sets, stochastic variables, auxiliary variables, and decision variables used in the model.

3.2.1. Parameters and Index Sets

(i) T Length of the multi-stage stochastic planning horizon.

(ii) t Decision time. $t = 0, 1, \ldots, T$

(iii) S Set of macro-scenario when corporation issuing new bonds.

(iv) S_{total} Total number of macro-scenario when corporation issuing new bonds.

s Scenario index.

(v) H Cash liquidity planning horizon of the corporation.

(vi) p^s Probability of the state associated with a scenario. s

(vii) J Set of variable fixed-rate bonds (with different issuance maturities issued by a corporation).

(viii) j Serial numbers of fixed-rate bonds issued by a corporation with different issuance maturities.

(ix) M_j Maturity of new bond j issued by the corporation.

(x) M_{old} Remaining maturity of the outstanding bonds that existed at the initial decision time.

(xi) NP_t^s Corporate average net profit for the last three years before time t under scenario s.

(xii) PS_t Corporate available cash surplus at time t.

(xiii) β^s Discount rate under scenario s.

(xiv) λ Ratio of the accumulated bond balance to the corporation's net assets.

(xv) CB_0 Cash balance of the corporation at the initial moment.

(xvi) $f_s(t)$ Amount of cash flow expected by the corporation at time t under scenario s.

The dependent inputs of the scenario are given below:

3.2.2. Stochastic Variables

(i) $r_{M_j,t}^s$ Coupon interest rate of bond j issued by the corporation at time t under scenario s.

(ii) $r_{w,t}^s$ One-year treasury bond yield at time t under scenario s.

(iii) L_t^s Liquidity payments amount of the corporation at time t under scenario s.

The decision variables are defined for each node of the scenario tree:

3.2.3. Decision Variable. X_{t,M_j}^s Amounts of types j of bonds issued by corporations at time t under scenario s.

The auxiliary variables are defined for each node of the scenario tree:

3.2.4. Auxiliary Variables

(i) DEBT_t^s Total number of bonds of the corporation at time t under scenario s.

(ii) ASSET_t^s Corporate net assets at time t under scenario s.

(iii) $\mathrm{cost\_}i_t^s$ Amount of bond interests that the corporation has to pay at time t under scenario s.

(vi) D_t^s Sum of the principal discounted of all new bonds issued by the corporation at time t to time 0 under scenario s.

(v) D_H^s Sum of the principal discounted to the initial stage of all old and new bonds mature within H under scenario s.

(vi) C_t^s Corporate cash amount at time t under scenario s.

(vii) $FB_{t,j}^{s,i}$ Amount of j bonds issued at time t and the remaining financing balance after the interest paid in year $t+i$ under scenario s.

(viii) $I_{t,i}^{s,j}$ Annual interests paid by the corporate bonds at time t is discounted to the amount at time 0 under scenario s.

(ix) I_t^s The sum of the discounted net interests of new bonds issued at time t to time 0 under the scenario. s

(x) I_H^s Sum of the interests of all outstanding bonds and the net interests of newly issued bonds during the period discounted to the initial stage under scenario s.

(x) I_{old} Outstanding bond interests that existed at the initial decision time.

(xi) $NI_{t,t+1}^s$ Non-bond cash inflows of the corporation from t to t+1, under scenario s.

(xii) $X_{t,t+1,j}^s$ Amount of types of bonds issued by corporations from t to t+1 under scenario s.

(xiii) $L_{t,t+1}^s$ Liquidity payments amount of the corporation from t to t+1, under scenario s.

(xiv) L_H^s Sum of the liquidity payment amount of the corporation within H under scenario s.

(xv) TC^s Total cost of issuing new bonds under scenario s.

(xvi) OLD_t^s Total amount of outstanding bonds issued by the corporation at time t under scenario s.

(xvii) CB_t^s Corporation's available cash balance at time t under scenario s.

(xviii) FLR Variables used in the definition of conditional financial leverage risk equal to VaR under the optimal solution.

(xix) PR Variables used in the definition of conditional payment-at-risk (similar to FLR).

3.3. Constraints. Our corporate bond issuance strategy management model is subject to three types of constraints:

(i) Balance constraints on the payments of principals and net interests of newly issued bonds by the corporation.

(ii) Balance constraints on the state of corporate cash flow.

(iii) Government constraints on the number of bonds issued by corporations.

3.3.1. Balance Constraint Equation for the Payments of Principals and Net Interest of Newly Issued Bonds. The balance constraint equation for the payments of the principals and net interests of newly issued bonds represents the corporate repayment cost and lays the foundation for the balance constraint equation for the corporate cash flow state.

(i) Total discounted principal value at the initial decision node of bonds issued at time t under scenario s:

$$D_t^s = \sum_{j\in J} \frac{X_{t,M_j}^s}{\left(1+\beta^s\right)^{Tj+t}}. \tag{1}$$

Based on the bond maturity, we can obtain the discounted value at the initial decision node of the principals of the bonds issued at time t. This equation sums up all the discounted principal values of each bond issued at time t for a specific scenario s. It is worth noting that in the calculation process, the WACC of the corporation under scenario s is used as the discount rate β^s.

(ii) Under scenario s, the total discounted interest at the initial decision node of bonds issued at time t:

$$I_{t,i}^{s,j} = \sum_{j\in J}\sum_{i=1}^{T_j} \frac{X_{t,M_j}^s \cdot r_{M_j,t}^s}{\left(1+\beta^s\right)^{i+t}}. \tag{2}$$

The discounted value at the initial decision node of the interests of bonds issued at time t can be calculated by the coupon rates and maturity of the bonds. Equation (2) sums the discounted interest value of all bonds issued at time t under a specific scenario s.

(iii) Under scenario s, the total discounted net interest at the initial decision node of bonds issued at time t:

$$\left.\begin{aligned} FB_{t,j}^{s,i} &= X_{t,M_j}^{s} - i \cdot I_{t,i}^{s,j}, \\ DF_t^{s,i} &= \frac{r_{w,t}^{s}}{\left(1+\beta^{s}\right)^{i+t}}, \\ R_t^{s} &= \sum_{j\in J}\sum_{i=1}^{T_j}\left(\left(FB_{t,j}^{s,i} + r_{w,t}^{s}\cdot\left(FB_{t,j}^{s,i-1}\right)\right)\cdot DF_t^{s,i}\right)(i\geq 1) \\ R_t^{s} &\geq 0 \end{aligned}\right\}, \tag{3}$$

where $FB_{t,j}^{s,i}$ represents the balance of financing after paying interests in year $t+i$ under scenario s, and $DF_t^{s,i}$ is a deposit discount factor. Formula (3) represents the cash deposits due to issuing bonds, it depends on $FB_{t,j}^{s,i}$ and $r_{w,t}^{s}$ as well as the discount factor $DF_t^{s,i}$.

$$I_t^{s} = \sum_{j\in J} I_{t,i}^{s,j} - R_t^{s}. \tag{4}$$

Equation (4) is the net interest cash flow equation for a corporation issuing new bonds under scenario s, which consists of the discounted interest of newly issued bonds and the cash deposits due to issuing bonds before repaying the principals of the bonds.

3.3.2. Balance Constraint Equation for Corporate Cash Flow. The balance constraint equation for corporate cash flow takes into account corporate cash liquidity, and the cash flow can be calculated on the basis of the balance state of the cash account each year.

Cash flow balance equation for a single corporation:

$$C_{t+1} = \sum_{j\in J} X_{t,t+1,M_j}^{s} + C_t^{s} + NI_{t,t+1}^{s} - L_{t,t+1}^{s} \quad \forall t, s. \tag{5}$$

The cash flow balance (5) shows that under scenario s, the cash balance of the corporation at t+1 equals the sum of the cash balance account at time t and the difference between cash inflow and cash outflow from t to t+1; here, the cash inflow includes corporate debt financing cash $\sum_{j\in J} X_{t,t+1,j}^{s}$ and non-bond cash inflow $NI_{t,t+1}^{s}$. $L_{t,t+1}^{s}$ represents cash liquidity payments from t to t+1.

3.3.3. Government Constraints on the Number of Bonds Issued by Corporations. In China, the number of corporate bonds that a corporation can be issued is subject to the following governmental restrictions. The average distributable profit of the corporation in the last 3 years must be sufficient to pay the interest on corporate bonds for 1 year, and the cumulative bond balance must not exceed 40% of net corporate assets (excluding minority shareholders' equity).

Below are mathematical descriptions of the constraint equations of our model:

(i) Principle of non-negativity (constraints on the number of corporate bonds):

$$X_{t,M_j}^{s} \geq 0. \tag{6}$$

(ii) Principle of market discipline:

$$\sum_{j\in J} X_{t,M_j}^{s}\cdot r_{M_j,t}^{s} \leq NP_t^{s}, \tag{7}$$

where NP_t^{s} represents the average distributable profit (net profit) for the 3 years before time t under the scenario s. Formula (7) shows that the average net profit for the 3 years before time t is enough to pay the interest on corporate bonds for 1 year.

(iii) Constraints on the amount of accumulated outstanding bonds: The government controls the leverage ratio to ensure that the corporation has an appropriate cash flow to deal with unexpected crises.

$$\begin{aligned} \mathrm{DEBT}_t^{s} &= \sum_{j\in J} X_{t,M_j}^{s} + \mathrm{OLD}_t^{s}, \\ \mathrm{ASSET}_t^{s} &= C_t^{s} + NI_{t,t+1}^{s} + \frac{1}{S}\cdot\left(\sum_{K=1}^{T}\frac{f_k^{s}}{\left(1+\beta^{s}\right)^{k}}\right), \\ \lambda &= \frac{\mathrm{DEBT}_t^{s}}{\mathrm{ASSET}_t^{s}}, \end{aligned} \tag{8}$$

λ is the corporate bond leverage ratio such that $0\leq\lambda\leq\overline{\lambda}$, where $\overline{\lambda}$ is the maximum debt ratio specified by the government, meaning that the accumulated outstanding bonds do not exceed $\overline{\lambda}$ of corporate net assets (excluding minority shareholders' equity).

3.4. Basic Concepts. Our model has three basic components: expected discounted cost, financial leverage risk, and cash liquidity risk.

3.4.1. Expected Discounted Cost. The expected discounted cost is the sum of the discounted costs of all bonds with different maturities issued at each decision time during the planning horizon [46]. For simplicity, we assume that the discount factor is fixed across the decision period and use the same discount factor to calculate the discounted costs of newly issued bonds with different maturities. For convenience, we regard all newly issued bonds of different maturities at the same decision time as one bond portfolio. The expected discounted cost of bonds issued within the planning horizon is the sum of the discounted costs of issuing bonds in the bond portfolio at each decision time.

We denote TC_t^{s} as the discounted cost at the initial decision time when issuing a new bond portfolio at time t under the scenario s,

$$\begin{aligned} TC_t^{s} &= D_t^{s}(x) + I_t^{s}(x), \\ TC^{s} &= \sum_{t=1}^{T} TC_t^{s}, t = 1, 2, \ldots, T, \end{aligned} \tag{9}$$

where TC^s represents the total discounted cost at the initial decision time of newly issued bonds within the decision horizon. Formula (9) shows that the discounted cost to be repaid by the corporation is the sum of the principals and interests in the bond portfolio et al. l decision-making points under the scenario s.

We focus on the expected discounted cost of bond portfolios at the initial decision time in each scenario within the decision horizon,

$$\text{COST} = \sum_{s \in S} p^s \cdot TC^s, \tag{10}$$

where p^s is the occurrence probability under the scenario s.

3.4.2. Financial Leverage Risk in-a Worst-Case Scenario. Traditionally, corporate financial leverage risk is measured by the degree of financial leverage (*DFL*) (Xu, Gunarathna, Balasubramaniam et al.) [47–49]. *DFL* is a leverage ratio that measures the sensitivity of a corporation's earnings per share to fluctuations in its operating income as a result of changes in its capital structure. It is determined by the ratio of earnings before interest and tax (*EBIT*) to post-interest profit. The *DFL* of a corporation at the time t under scenario s is

$$\begin{aligned} DFL_t^s &= \frac{EBIT_t^s}{\left(EBIT_t^s - \text{Interest}_t^s\right)}, \\ \text{Interest}_{t+1}^s &= \sum_{j \in J}\left(X_{t,M_j}^s \cdot r_{M_j,t}^s\right) + \sum_{j \in J}\left(X\_B_t^s \cdot r\_B_t^s\right), \end{aligned} \tag{11}$$

where $EBIT_t^s$ is earnings before interest and taxes at the time t, $\text{Interest}_{t+1}^s(x)$ is the amount the corporation needs to pay at time t+1, $\sum_{j \in J}(X\_B_t^s \cdot r\_B_t^s)$ is the interest paid on outstanding bonds at time t+1 except for those issued at time t, and $\sum_{j \in J}(X_{t,M_j}^s \cdot r_t^{M_j})$ is the number of interest payments at time t+1 of the bond portfolio issued at time t.

The degree of financial leverage cannot reflect the real level of financial leverage risk caused by some extreme events. These extreme events often emerge as fat tails, and tail risk can be measured by conditional value-at-risk (*CVaR*) (see Pflug, 2000; Uryasev and Rockafellar, Mansini et al; Agarwal and Naik, Liang and Park) [50–54]. Moreover, known as "expected shortfall," *CVaR* is derived by taking the weighted average of "extreme" losses in the tail of the distribution of possible returns. Building on *CVaR*, we formulate the construct of conditional financial leverage risk (*CFLaR*) to measure the financial leverage risk faced by a corporation in a worst-case scenario. Essentially, *CFLaR* extends *CVaR* by considering the size of the financial leverage ratio beyond a given *DFL* faced by the corporation at the end of year t. To compute the value of *CFLaR*, we define an auxiliary variable *FLR* that represents a certain financial leverage risk for a given level α, and we denote *CFLaR* as

$$CFLaR = FLR(\alpha) + \frac{1}{(1-\alpha)} \cdot \frac{1}{S} \cdot \sum_{s=1}^{S} \left(DFL_t^s - FLR(\alpha)\right)^+, \tag{12}$$

where $(DFL_t^s - FLR(\alpha))^+ = \max\{DFL_t^s(x) - FLR(\alpha), 0\}$. Thus, *CFLaR* is the extended risk measure of *DFL* that quantifies the average *DFL* values that exceed a given *FLR* (α) value, and it accounts for the expected possible *DFL* level in a worst-case scenario.

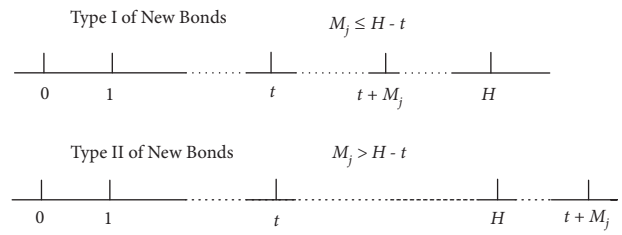


Figure 2: The new bonds are issued at time t within the cash liquidity planning horizon (H).

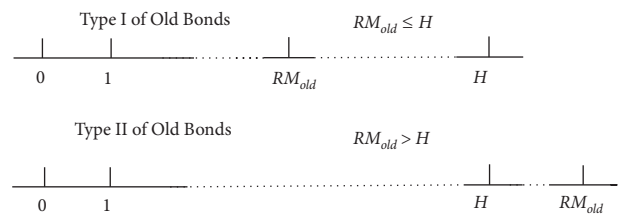


Figure 3: The old outstanding corporate bonds were issued before the initial decision time 0 but still existed at the initial decision time 0 within the cash liquidity planning horizon (H).

3.4.3. Corporate Short-Term Cash Liquidity Risk in Worst-Case Scenario. Cash liquidity risk is associated with a corporation's actual debt repayments and total cash flow. In practice, corporations tend to focus on short-term liquidity risk. Here, short-term liquidity is quantified as corporate liquidity income and expenses within a certain period (Owolabi and Obida) [55]. To accurately measure the short-term liquidity risk of a corporation over some time, we consider a corporation's short-term liquidity risk during a cash liquidity planning period H and assume that H is longer than the multistage stochastic planning horizon.

We identify two types of bond payments during H. The first is the payment of newly issued bonds at a time t within H. The second is the payment of outstanding corporate bonds that were issued before the initial decision time 0 but exist at the initial decision time 0 within H. For convenience, we denote these two types of bond payments as "new bonds" and "old bonds," respectively and divide "new bonds" and "old bonds" both into a further two types. New bonds issued at time t that mature within H are the first type of new bonds. New bonds issued at time t that mature beyond H are the second type of new bonds. The first type of old bonds is outstanding bonds issued before the initial decision time 0 that still exist at the initial decision time 0 and mature within H, while the second type of old bonds is outstanding bonds issued before the initial decision time 0 that still exist at the initial decision time 0 and mature beyond H. The classification of "new bonds" can be seen in Figure 2, and the classification of "old bonds" is shown in Figure 3.

Therefore, we denote $D_H^s(x)$ as the discounted bond principal payment at the initial decision time 0 during H as follows:

$$\left.\begin{aligned}
&D_H^s(x) = \sum_{M_j \le H-t} \frac{X_{t,M_j}^s}{(1+\beta^s)^{M_j}} \cdot 1_{A_1}(M_j) + \sum_{RM_{\text{old}} \le H} \frac{DEBT_{\text{old}}}{(1+\beta^s)^{RM_{\text{old}}}} \cdot 1_{A_2}(M_{\text{old}}), \forall s \in S \\
&A_1 = \{M_j\colon M_j \le H-t\} \\
&A_2 = \{M_{\text{old}}\colon M_{\text{old}} \le H\} \\
&1_A(\omega) = \begin{cases} 1 & \omega \in A \\ 0 & \omega \notin A \end{cases}
\end{aligned}\right\}, \tag{13}$$

where

(i) DEBT_{old} denotes the principals of outstanding bonds that exist at the initial decision time.

(ii) RM_{old} is the remaining maturity of outstanding bonds at the initial decision time.

(iii) $\sum_{M_j \le H-t} X_{t,M_j}^s / (1+\beta^s)^{M_j} \cdot 1_{\{M_j \le H-t\}}$ is the discounted principals of new corporate bonds issued at time t within H.

(iv) $\sum_{RM_{\text{old}} \le H} DEBT_{\text{old}} / (1+\beta^s)^{RM_{\text{old}}}$ is the discounted principals of outstanding bonds issued before the initial decision time 0 that exists at the initial decision time 0 within H.

$D_H^s(x)$ is the sum of $\sum_{M_j \le H-t} X_{t,M_j}^s / (1+\beta^s)^{M_j}$ and $\sum_{RM_{\text{old}} \le H} DEBT_{\text{old}} / (1+\beta^s)^{RM_{\text{old}}}$ during H.

We denote $I_H^s(x)$ as discounted bond interest payment at the initial decision time 0 during H:

$$\left.\begin{aligned}
&I_H^s(x) = \sum_{M_j \le H-t} \sum_{i=1}^{M_j} \frac{X_{t,M_j}^s \cdot r_{M_j,t}^s}{(1+\beta^s)^{i+t}} \cdot 1_{A_1}(M_j) + \sum_{M_j > H-t} \sum_{i=1}^{H-t} \frac{X_{t,M_j}^s \cdot r_{M_j,t}^s}{(1+\beta^s)^{i+t}} \cdot 1_{A_3}(M_j) + \\
&\sum_{RM_{\text{old}} \le H} \sum_{i=1}^{RM_{\text{old}}} \frac{I_{\text{old}}}{(1+\beta^s)^i} \cdot 1_{A_2}(RM_{\text{old}}) + \sum_{RM_{\text{old}} > H} \sum_{i=1}^{H} \frac{I_{\text{old}}}{(1+\beta^s)^i} \cdot 1_{A_4}(RM_{\text{old}}) \\
&\forall s \in S \\
&A_3 = \{M_j\colon M_j > H-t\} \\
&A_4 = \{M_{\text{old}}\colon M_{\text{old}} > H\} \\
&1_A(\omega) = \begin{cases} 1 & \omega \in A \\ 0 & \omega \notin A \end{cases}
\end{aligned}\right\}, \tag{14}$$

where I_{old} is the outstanding bond interest that exists at the initial decision time 0. For convenience, we define the first type of new bonds as those issued at time t that matures within H. We define the second type of new bonds as those issued at time t that matures beyond H. We define the first type of old bonds as those outstanding at the initial decision time that matures within H; and the second type of old bonds is defined as those outstanding at the initial decision time that matures beyond H. In the above formulation (20):

(i) $\sum_{M_j \le H-t} \sum_{i=1}^{M_j} X_{t,M_j}^s \cdot r_{M_j,t}^s / (1+\beta^s)^{i+t} \cdot 1_{A_1}(M_j)$ is the discounted interest payments at the initial decision time of the first type of new bonds during H.

(ii) $\sum_{M_j > H-t} \sum_{i=1}^{H-t} X_{t,M_j}^s \cdot r_{M_j,t}^s / (1+\beta^s)^{i+t} \cdot 1_{A_3}(M_j)$ is the discounted interest payments at the initial decision time of the second type of new bonds during H.

(iii) $\sum_{RM_{\text{old}} \le H} \sum_{i=1}^{RM_{\text{old}}} I_{\text{old}} / (1+\beta^s)^i \cdot 1_{A_2}(RM_{\text{old}})$ is the discounted interest payments at the initial decision time 0 of the first type of outstanding bonds during H.

(iv) $\sum_{RM_{\text{old}} > H} \sum_{i=1}^{H} I_{\text{old}} / (1+\beta^s)^i \cdot 1_{A_4}(RM_{\text{old}})$ is the discounted interest payments at the initial decision time 0 of the second type of outstanding bonds during H.

We use conditional payment-at-risk ($CPaR$) to measure the highest possible payment level in a worst-case scenario:

$$CPaR(\alpha) = PR(\alpha) + \frac{1}{(1-\alpha)} \cdot \frac{1}{S} \cdot \sum_{s=1}^{S} \left(D_H^s(x) + I_H^s(x) + L_H^s - PR(\alpha)\right)^+, \tag{15}$$

where PR is the value of cash liquidity payments for a given level α, and $(D_H^s(x) + I_H^s(x) + L_H^s - PR(\alpha))^+ = \max(D_H^s(x) + I_H^s(x) + L_H^s - PR(\alpha), 0)$. That is, $CPaR$ is the average liquidity payment value paid by a corporation when the corporate liquidity payment exceeds a given PR value during H. The above-mentioned $CPaR$ formula considers the expected possible payment level of a corporation during H in a worst-case scenario. Corporations can compare the value of $CPaR$ with the level of funds that they generate under extreme market conditions to manage liquidity risks.

4. Objective Functions

In the real world, bond issuance managers mainly focus on bond repayment cost ($COST$), financial leverage risk in worst-case scenarios ($CFLaR$), and short-term cash liquidity risk in worst-case scenarios ($CpaR$). To meet the specific requirements of their corporations, managers usually prioritize the following three common cases about objective functions.

Case I. Minimizing $COST$ under the constraints of different $CFLaR$ and $CPaR$.

Under the constraints of different $CFLaR$ and $CPaR$, we minimize $COST$ in the debt planning horizon as follows:

$$\min_{x_{t,m_j}^s, s \in S} \text{COST},$$
$$s.t. \begin{cases} \underline{b} \le CFLaR \le \overline{b}, \\ \underline{c} \le CPaR \le \overline{c}, \\ \sum_{j \in J} x_{t,m_j}^s = X_t, \\ \underline{b} \ge 0, \\ \underline{c} \ge 0, \end{cases} \tag{16}$$

where $\underline{b}$ and $\overline{b}$ are the lower and upper thresholds of $CFLaR$, respectively, $\underline{c}$ and $\overline{c}$ are the lower and upper thresholds of CPaR, respectively, and $X_t \ge 0$, X_t is the financing size at decision time t.

Case II. Minimizing $CFLaR$ under the constraints of different COST and $CPaR$.

Similarly, we minimize the financial leverage risk $CFLaR$ under the constraints of different COST and $CPaR$ in the debt planning horizon as follows:

$$\min_{x_{t,m_j}^s, s \in S} CFLaR(\alpha),$$
$$s.t. \begin{cases} \underline{a} \le \text{COST} \le \overline{a}, \\ \underline{c} \le CPaR \le \overline{c}, \\ \sum_{j \in J} x_{t,m_j}^s = X, \\ \underline{a} \ge 0, \\ \underline{c} \ge 0, \end{cases} \tag{17}$$

where $\underline{a}$ and $\overline{a}$ are the lower and upper thresholds of COST, respectively.

Case III. Minimizing $CPaR$ under the constraints of different $COST$ and $CFLaR$.

We minimize the corporate cash liquidity risk ($CPaR$) under the constraints of different $COST$ and $CFLaR$ in the debt planning horizon as follows:

$$\min_{x_{t,m_j}^s, s \in S} CPaR,$$
$$s.t. \begin{cases} \underline{a} \le CPaR \le \overline{a}, \\ \underline{b} \le CFLaR \le \overline{b}, \\ \sum_{j \in J} x_{t,m_j}^s = X, \\ \underline{a} \ge 0, \\ \underline{b} \ge 0. \end{cases} \tag{18}$$

5. Empirical Analysis

We empirically test the model proposed in Section 4 by applying it to the Chinese company Zhejiang Oriental Holding Group Co., Ltd. (ZOH), whose credit rating is AAA. For convenience, we assume that ZOH company makes an annual issuance plan at the beginning of each year and that the plan can be revised at the beginning of the following year on the basis of the company's finances. ZOH has three outstanding bonds, comprising one medium-term bond and two short-term bonds (see Table 1).

Based on the information on these outstanding bonds, we make the following assumptions:

(i) We assume that the company issues 1 billion bonds each year in three stages (3 years).

(ii) Our model presents a selection of four types of bonds, 3-year, 5-year, 10-year, and 15-year maturity

Table 1: Basic Information of outstanding bonds issued by ZOH company.

	Bond I (21 Dongfang01)	Bond II (20 Dongfang01)	Bond III (20 Dongfang02)
Category of coupon rate	Fixed rate	Fixed rate	Progressive interest rate
Coupon rate (year)	3.9% (2022–2024)	3.63% (2021–2023)	3.4% (2021, 2022, 2023) 3.4% +Basis point (2024, 2025)
Remaining maturity	2.781 Years	1.523 Years	3.929 Years
Issuance size	1 billion yuan	1 billion yuan	0.5 billion yuan

bonds, based on the actual portfolios of bonds issued by ZOH.

(iii) Because the length of our multistage stochastic planning horizon is 3 years, we set the cash liquidity planning horizon H as 6 years to examine corporate cash payments in the current three-stage stochastic planning horizon and the following three-stage stochastic planning horizon.

(iv) We calculate *CPaR* and *CFLaR* at the 95th percentile of their respective distributions (i.e., $\alpha = 5\%$) .

(v) For simplicity, we set the issuance strategy in each year as time-variant, i.e., the weight of each maturity bond is unfixed within the planning horizon.

(vi) The interest payments of outstanding bond II (20 Dongfang01), which matures in the second year, are not paid; therefore, the interest payments of outstanding bond III (20 Dongfang02) will increase in the third year. For convenience, we assume that the total interest payments for outstanding bonds in each year are stable across the three stages.

Next, we describe our method of generating scenario trees to simulate the paths of relevant macroeconomic variables.

5.1. Generation of Scenario Trees. We generate our scenario trees by filtered historical simulation (FHS), which combines a relatively sophisticated model-based treatment of volatility (generalized autoregressive conditional heteroskedasticity) with a nonparametric specification of the probability distribution of asset returns (Anderson, Høyland Wallace, and Tao et al.) [56–58]. Compared with other simulation methods, such as traditional historical simulation and Monte Carlo simulation, FHS has two advantages (Roy) [59]. First, it can capture the conditional heteroskedasticity in the data and be unrestrictive about the shape of the distribution of the risk factors. Second, the method does not involve the estimation of the correlation matrix of risk factors.

The scenario trees generated for the three associated stochastic variables, comprising the coupon rates of newly issued fixed-rate corporate bonds, *EBIT*, and 1-year treasury bond yield, demonstrate the potential evolution of the path of each variable into the future. The three scenario trees help us to measure COST, *CFLaR*, and *CPaR* and examine their relationships with different constraints. For instance, we can use the FHS technique (Pritsker) [60] to simulate a scenario tree of coupon rates based on historical data on forward yields. Specifically, we assume that the conditional mean and variance-covariance matrix of the market forward yields of different bond maturities depend on the history of the market forward yields. r_t is the coupon rate at time t and h_{r_t} is the historical data on the market forward yields of bonds before time t. We define θ as the parameters of the market forward yields generation process; $\mu(h_{r_t}, \theta)$ represents the mean of the yields at time t, conditional on the history of market forwarding yields and θ; $\sum(h_{r_t}, \theta)$ is the variance-covariance matrix of r_t, conditional on h_{r_t} and θ. The coupon rate r_t is driven by the following equation:

$$r_t = \mu\left(h_{r_t}, \theta\right) + \sum\left(h_{r_t}, \theta\right) \cdot \epsilon_t, \tag{19}$$

where θ denotes the parameters of the conditional mean and volatility model and ϵ_t is independent and identically distributed through time with a mean of 0 and variance of I; the θ parameters can be estimated by quasimaximum likelihood under appropriate regularity conditions. Because h_{r_t} is observable, ϵ_t can be identified, θ parameters can be estimated, and the FHS method can be implemented in more general cases. Based on historical data on the market forward yields of bonds with maturities of 3 years, 5 years, 10 years, and 15 years for the target corporation, which has an AAA credit rating, from October 2016 to April 2021, using (17), the scenario trees were generated using MATLAB 2018. It is worth noting that FHS can predict the future trend of corporate bond market forward yields with different maturities based on its historical data. In this paper, the market forward yield of corporate bonds with different maturities for each of the next three years can be simulated according to the historical data on corporate bond's market forward yields with different maturities, for example, the market forward yield of 3-year corporate bonds for each of the next three years can be simulated according to the historical data on 3-year corporate bond's market forward yields, and the forward market yield of corporate bonds can be used as the coupon rate for newly issued bonds. The bond issuance decision at each stage will be affected by the simulated changes in the market forward yield curve of different maturities, that is, the decision-makers in the next stage must take into account the changes in the coupon rate of bond portfolios with different maturities at the current stage and the previous stage when formulating the bond issuance strategy, this is achieved in the program code we designed.

5.2. Robustness Analysis of Scenario Tree Generation. Using FHS, historical data on corporate bond market forward yields (3-years, 5-years, 10-years, and 15-year) and 1 year treasury bond yields from October 2016 to April 2021, we generate three independent and identically distributed scenario trees within a 3 year planning period, and we test the robustness of the three given models in, and (10) and

Table 2: Robustness results.

Scenario tree	Case 1: Minimum of *COST* (billion yuan)		Minimum of *CPaR* (billion yuan)		Minimum of *CFLaR*	
	Average	St. Dev.	Average	St. Dev.	Average	St. Dev.
$10 \times 10 \times 10$	2.8821	0.0003	3.7450	0.0035	1.1367	0.000007
$20 \times 10 \times 10$	2.8720	0.0070	3.7473	0.0002	1.1380	0.000014
$30 \times 10 \times 10$	2.8808	0.0069	3.7453	0.0307	1.1375	0.000003
$50 \times 10 \times 10$	2.8739	0.0073	3.7392	0.0338	1.1378	0.000001
$80 \times 10 \times 10$	2.8720	0.0070	3.7369	0.0181	1.1367	0.0000001

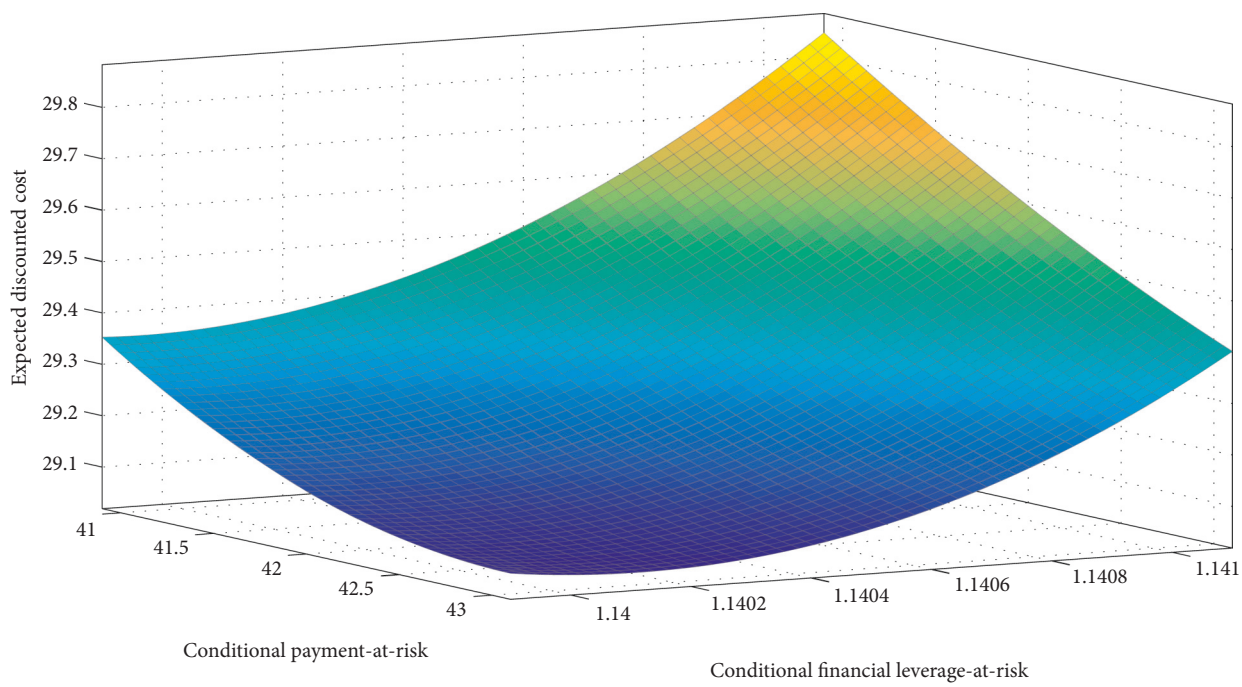


Figure 4: Efficient frontier of a minimum of **COST** with the different **CPaR** and **CFLaR** constraints.

(12), (13). All of the scenario trees are created within the same planning period (3 years); only the number of branches differs. For example, the notation $10 \times 10 \times 10$ corresponds to a three-stage tree with 10 branches from each node in each stage, with 1,000 branches in the final stage. Table 2 depicts the average and standard deviation of the minimum *COST*, *CPaR*, and *CFLaR*, respectively, within the 3-year planning period. The average minimum value of *COST* represents the lowest possible level of expected discounted cost, while the average minimum values of *CFLaR* and *CPaR* indicate the minimum level of corporate financial leverage risk and the minimum level of corporate cash liquidity risk, respectively, in worst-case scenarios.

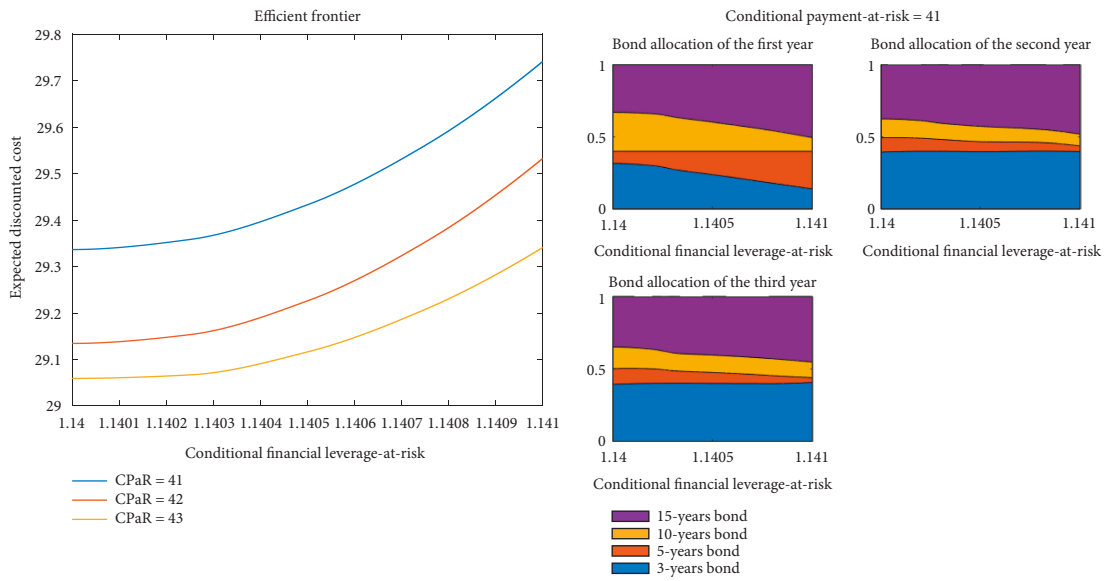
From Table 2, we find that the average minimum COST for ZOH company is approximately 2.8 billion yuan for 3 years , while the average minimum CPaR is around 3.7 billion yuan. The corresponding variance of minimum *COST*, *CFLaR*, and *CPaR* is very small, which shows that the scenario tree generation process is stable.

5.3. Empirical Results. We describe the empirical results for cases *I-III* (introduced in Section 4) in Section 5.3.1, Section 5.3.2, and Section 5.3.3, respectively.

5.3.1. Case 1: Minimizing COST under the Constraints of Different **CFLaR** *and* **CPaR**. For convenience, we examine the efficient frontier of minimum *COST* under the constraints of different $CPaR \in [41, 42]$ and $CFLaR \in [1.139, 1.141]$ and show our results in Figure 4.

As shown in Figure 4, the minimum COST increases with *CFLaR* and decreases as *CPaR* increases. *CFLaR* is generated by the interest payments of outstanding bonds and newly issued bonds; however, under the assumption that the total interest payments of outstanding bonds in each year are stable across the three stages, *CFLaR* is mainly determined by the interest payments of newly issued bonds. Furthermore, because the interest of long-term bonds is higher than that of short-term bonds, increasing the proportion of long-term bonds will cause *CFLaR* and minimum COST to increase. *CPaR*, which represents the average cash payment level in a worst-case scenario, and is mainly determined by the total payments of principals and interests associated with bonds that mature within H. Thus, increasing the proportion of long-term bonds will lead to a decrease in *CPaR* and an increase in minimum COST.

To explore the evolution of the efficient frontier more precisely, we examine different efficient frontier curves for minimum *COST* with two categories of constraints: (i)



(a) (b)

Figure 5: The efficient frontier curves of minimal **COST** under different **CFLaR** and three fixed **CPaR** = 40, 41, 42 (a), the optimal bond composition with constraints of **CPaR** = 41 and different **CFLaR** (b).

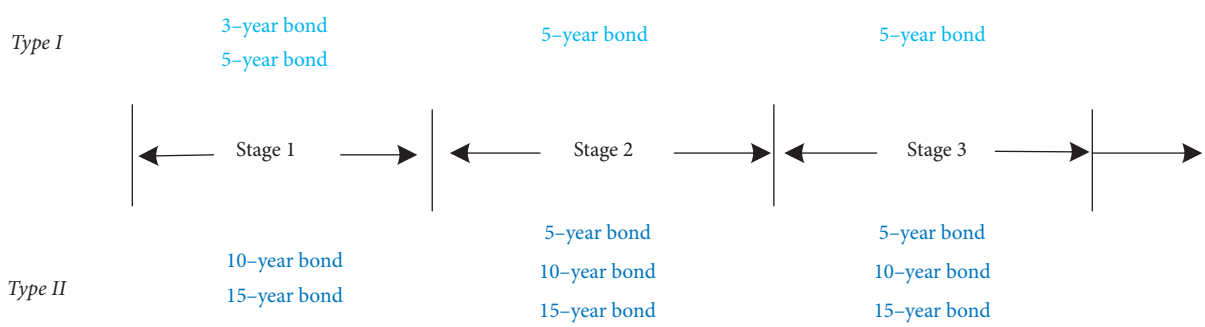


Figure 6: The bonds mature within the liquidity planning horizon **H** = 6 years (*Type I*) and the bonds mature after **H** = 6 years (*Type II*).

different $CFLaR$ and fixed $CPaR$; and (ii) different $CPaR$ and fixed $CFLaR$.

(i) The efficient frontier curves of the minimum of COST with constraints of different $CFLaR$ and three fixed $CPaR$.

Figure 5(a) depicts the corresponding efficient frontier curves for minimum COST under the constraints of different $CFLaR$ and three fixed $CPaR = 41, 42, 43$. As shown in Figure 5(a), each efficient frontier of minimum COST is an increasing function of $CFLaR$ under every fixed $CPaR$. An increase in $CFLaR$ represents an increase in the proportion of long-term bonds, which leads to an increase in minimum COST, and vice versa. To further examine the composition of optimal bond portfolios, we consider the example $CPaR = 41$ and give the corresponding issuance compositions in Figure 5(b).

Corresponding to a minimum COST with the constraints of different $CFLaR$ and fixed $CPaR = 41$, Figure 5(b) shows the optimal bond portfolio composition for each year of three-stage bond issuance with a 3 year planning horizon. We find all four types of bonds in the composition of bonds issued at each issuance stage.

To further explore the total payments of bonds issued within the three-stage bond issuance planning horizon when $H =$ 6 years, we divide bonds issued within the three-stage bond issuance planning horizon into the following two types (see Figure 6):

(i) *Type I*: Bonds that mature within the liquidity planning horizon when $H = 6$ years, including 3 year and 5 year bonds issued in the first year, 3 year bonds issued in the second year, and 3 year bonds issued in the third year.

(ii) *Type II*: Bonds that mature after the liquidity planning horizon when $H = 6$ years, including 10 year and 15 year bonds issued in the first year, 5 year, 10 year, and 15 year bonds issued in the second year, and 5 year, 10 year, and 15 year bonds issued in the third year.

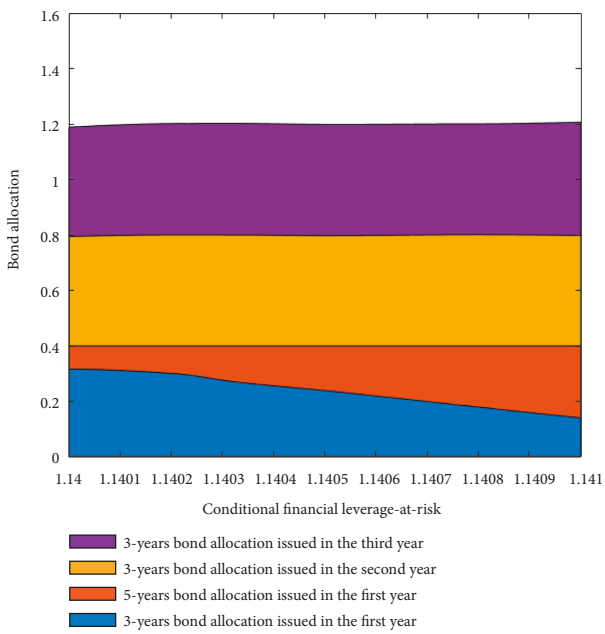


Figure 7: The total proportion of bonds that mature within the liquidity planning horizon **H** = *6* years under the fixed **CPaR** = 41.

Based on Figure 5(b), we derive the total proportion of *Type I* bonds as shown in Figure 7, including 3 year and 5 year bonds issued in the first stage, 3 year bonds issued in the second stage, and 3-year bonds issued in the third stage. Figure 7 shows that the total proportion of *Type I* bonds in the three stages is relatively stable. This can be explained as follows. Because *CPaR* is determined by the total payments of principal and interest of *Type I* bonds when the cash liquidity planning horizon $H = 6$ years, a fixed *CPaR* should be driven by the fact that the total payments of principal and interest associated with *Type 1* bonds in the three stages are fixed.

Regarding *CPaR* = 41, because 3 year and 5 year bonds represent nearly half of the total issued bond portfolio in Figure 5(b), assuming that the same amount of new bonds (1 billion yuan) is issued in each stage, the total issuance amount of 3 year and 5 year bonds is close to the total issuance amount of 10 year and 15 year bonds. Because a bond's interest payments are a very small proportion of its principal, the total interest payments of bonds can be ignored. Thus, for a fixed *CPaR* = 41, the total payment of principals of *Type I* bonds when the liquidity planning horizon $H = 6$ years should be stable, which is consistent with Figure 7.

(ii) The efficient frontiers of the minimum of COST with constraints of different *CPaR* and three fixed *CFLaR*.

Figure 8(a) shows the corresponding efficient frontier curves for minimizing COST with different *CPaR* and three fixed *CFLaR* = 1.14, 1.1405, 1.141. As shown in Figure 8(a), each efficient frontier of minimum COST is a decreasing function of *CPaR* under a fixed *CFLaR*. As mentioned above, *CPaR* is mainly determined by the total payments of principals associated with bonds that mature within *H*. An increase in *CPaR* means that the proportion of short-term bonds increases, which in turn decreases the minimum COST, and vice versa. To further explore the composition of optimal bond portfolios, we consider *CFLaR* = 1.141 and provide the corresponding composition in Figure 8(b).

Figure 8(b) shows the optimal bond portfolio composition corresponding to a minimum COST with the constraints of different CPaR and fixed *CFLaR* = 1.141 for each year of a three-stage bond issuance planning horizon. It shows that the portfolio includes all four types of bonds in each issuance year.

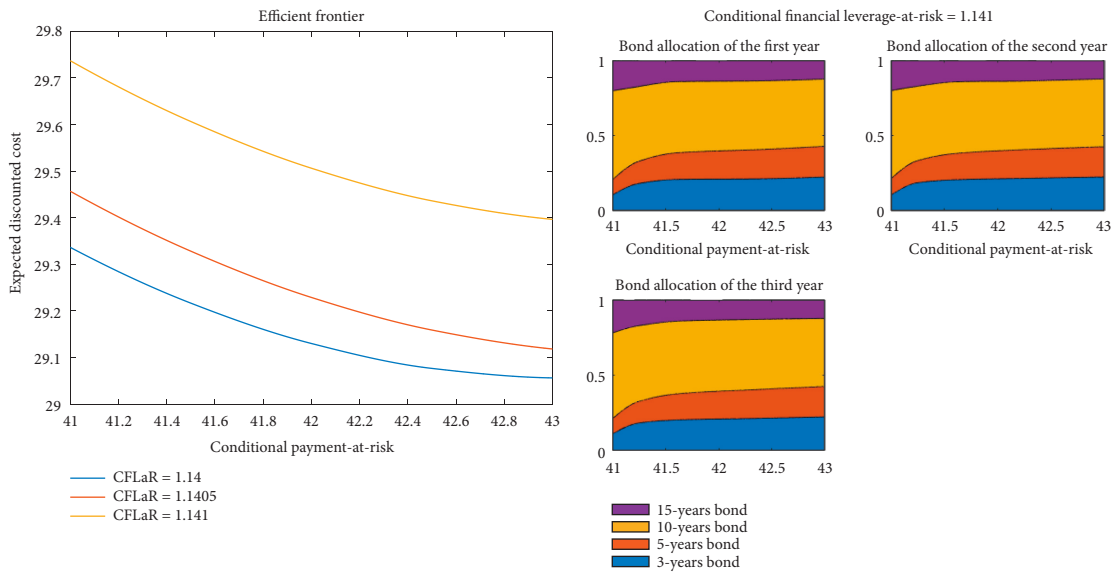
To explain the evolution of the slopes of the efficient frontier curves in Figure 8(a), we examine the total discounted payments of new bonds issued in three stages, which include all four bond types, and give the total proportion of each kind of newly issued bonds in Figure 9. As *CPaR* shifts from 41 to 43, the total proportions of 3 year and 5 year bonds in the three stages gradually increase, while the total proportions of 10 year and 15 year bonds in the three stages gradually decrease. Because COST is mainly determined by the discounted principal and interest payments of the newly issued bonds, increasing the proportion of long-term bonds leads to an increase in COST. The total proportion curve for each new bond becomes smooth as *CPaR* shifts from 41 to 43 in Figure 9. This shows that the incremental magnitude of the total proportions of 3-year and 5-year bonds gradually decreases, while the magnitude of the decrease in the total proportions of 10 year and 15-year bonds gradually decreases when the cash liquidity planning horizon $H = 6$ years. Consequently, the rate of decrease of minimum COST gradually falls, as shown in Figure 8(a).

5.3.2. Case 2: Minimizing **CFLaR** *under the Constraints of Different* **COST** *and* **CPaR**. Similar to Case 1, we examine the efficient frontier of minimum *CFLaR* with the constraints of different $CPaR \in [41, 43]$ and different $\text{COST} \in [29, 30]$, as shown in Figure 10.

As shown in Figure 10, the minimum *CFLaR* increases as COST increases and decreases as *CPaR* increases. COST is determined by the discounted principals and interests of newly issued bonds during the three stages. The discounted principals and interests of short-term bonds are both smaller than those of long-term bonds when the issued amounts of short- and long-term bonds are the same; therefore, an increase in the proportion of long-term bonds leads to an increase in COST. As in Case 1, minimum *CFLaR* increases with the proportion of long-term bonds, while an increase in the proportion of long-term bonds causes *CPaR* to decrease.

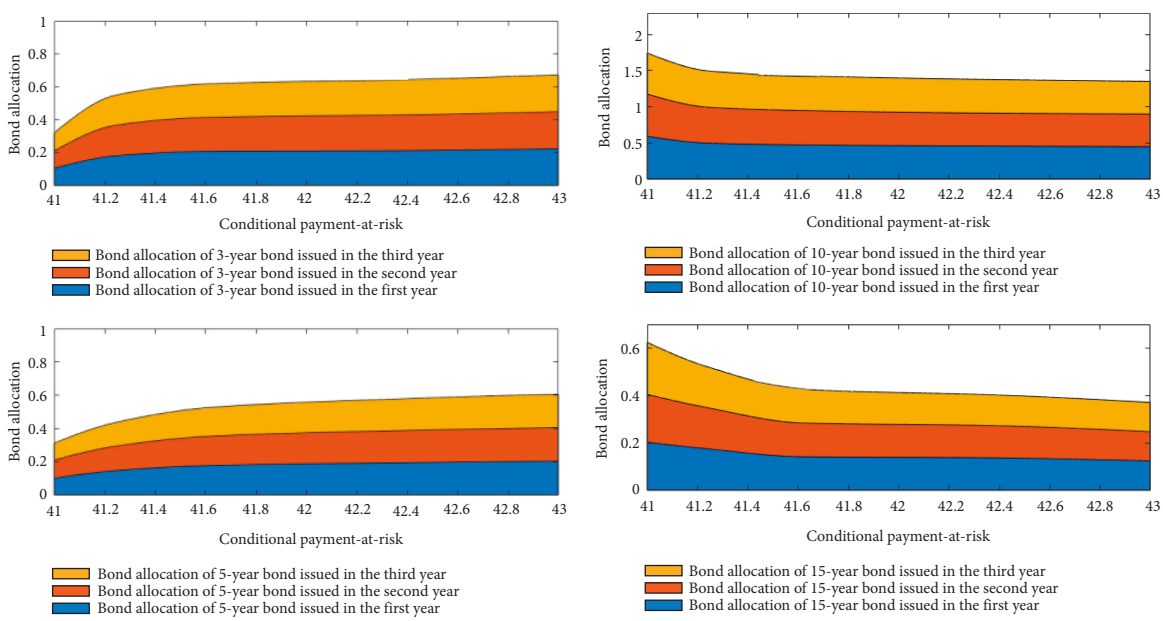
Again, to explore the evolution of the efficient frontier more precisely, we consider two types of constraints: (i) different COST and fixed *CPaR*; and (ii) different *CPaR* and fixed COST.

(i) The efficient frontier curves of the minimum of *CFLaR* with constraints of different COST and three fixed *CPaR*.



(a) (b)

Figure 8: The efficient frontier curves to minimize the **COST** with the different **CPaR** and three fixed **CFLaR** = 1.14, 1.1405, 1.141 (a), the optimal bond composition with constraints of **CFLaR** = 1.141 and different **CPaR** (b).



(a) (b)

Figure 9: The total proportion of each kind of new issue which includes issued in the three stages as **CPaR shift** from 41 to 43.

Figure 11(a) shows the efficient frontier curves for minimum *CFLaR* under different COST and three fixed *CPaR* = 41, 42, 43. Each efficient frontier of minimum *CFLaR* is an increasing function of COST under a fixed *CPaR*. Regarding the bond portfolio composition, the proportion of long-term bonds increases as COST gradually increases, and an increase in the proportion of long-term bonds leads to an increase in minimum *CFLaR*, and vice versa. We also provide the optimal bond issuance compositions for *CPaR* = 41 in Figure 11(b).

Figure 11(b) displays the optimal bond portfolio compositions for each year of the three-stage bond issuance period within a 3-year planning horizon under fixed *CPaR* = 42, which include all four types of bonds at each issuance stage.

We further analyze the total payments of bonds issued within the three-stage bond issuance planning horizon when $H = 6$ years, showing the total proportion of *Type I* bonds in Figure 12. Although the proportion of each of the *Type I* bonds in the three stages is time-variant as COST shifts from 29 to 30,

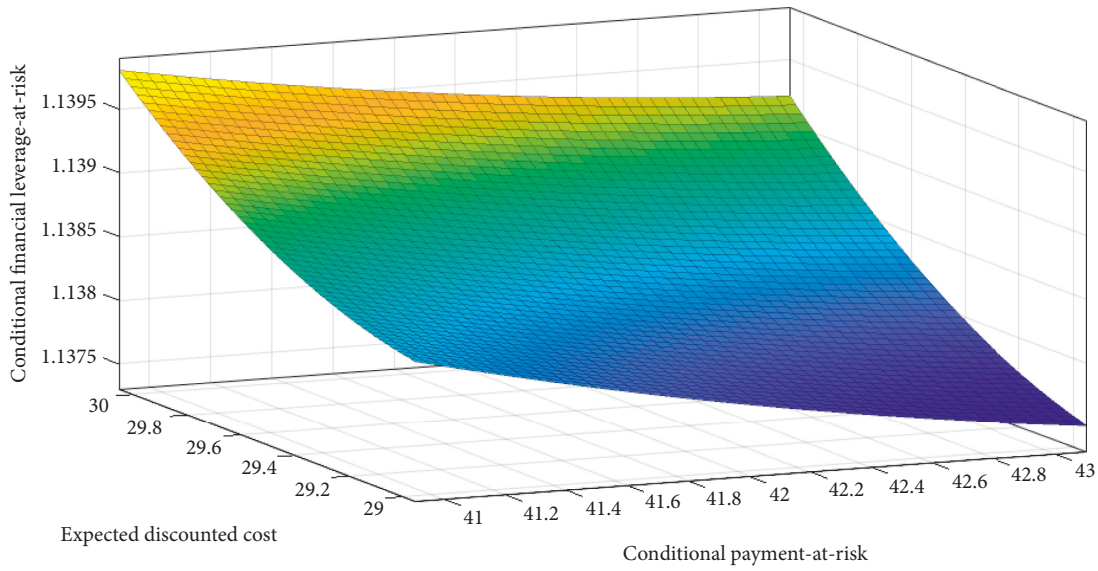


Figure 10: Efficient frontier of a minimum of **CFLaR** with different **CPaR** and **COST** constraints.

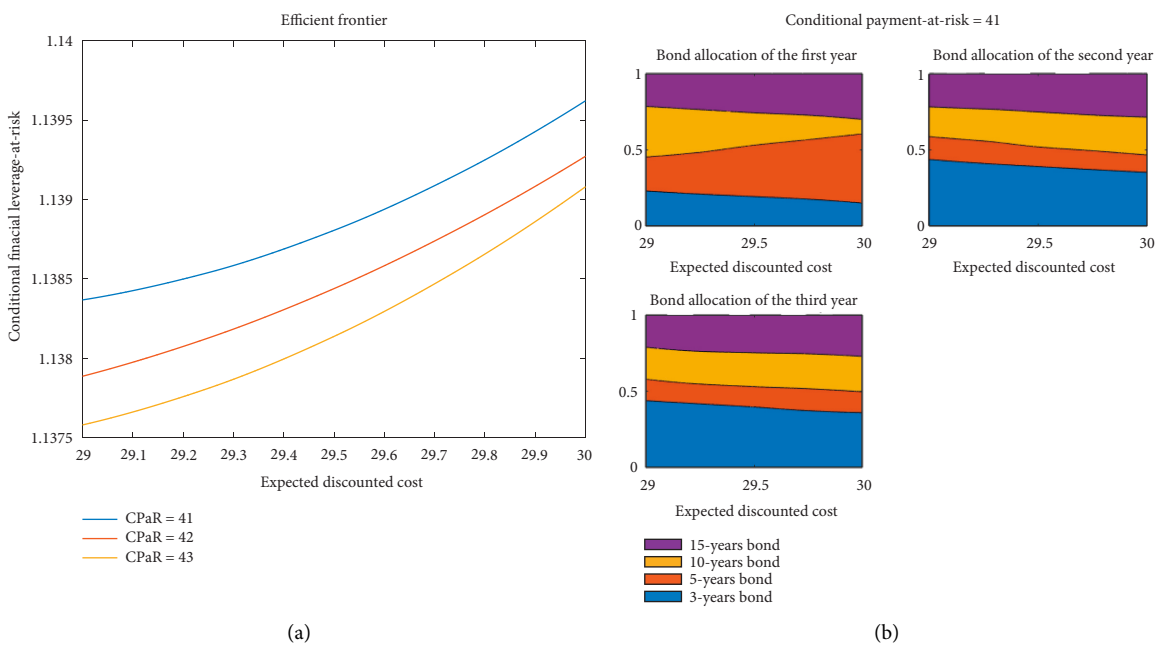


Figure 11: The efficient frontier curves of the minimum of **CFLaR** under different **COST** and three fixed **CPaR** = 41, 42, 43 (a), the bond composition with **CPaR** = 42 and different **COST** (b).

the total proportion of *Type I* bonds in the three stages is relatively stable. A fixed *CPaR* should be driven by the total payments of principals associated with *Type I* bonds in the three stages. When *CPaR* is fixed in each stage, the total proportion of *Type I* bond principals should be relatively stable for a liquidity planning horizon $H = 6$ years, regardless of whether the proportion of each *Type I* bond is stable. This is consistent with Figure 11(a).

(ii) The efficient frontiers of the minimum of *CFLaR* with constraints of different *CPaR* and three fixed COST.

Figure 13(a) shows the efficient frontier curves for minimum *CFLaR* with different *CPaR* and three fixed COST = 29, 29.5, 30. As shown in Figure 13(a), each efficient frontier of minimum *CFLaR* is a decreasing function with respect to *CPaR* under a fixed COST. As in Case 1, *CPaR*, which is mainly decided by the total proportion of *Type I* bonds in the three stages, increases with the proportion of short-term bonds, and an increase in the proportion of short-term bonds leads to a decrease in minimum *CFLaR*, and vice versa. We examine the composition of the optimal bond portfolio again for COST = 30, as shown in Figure 13(b).

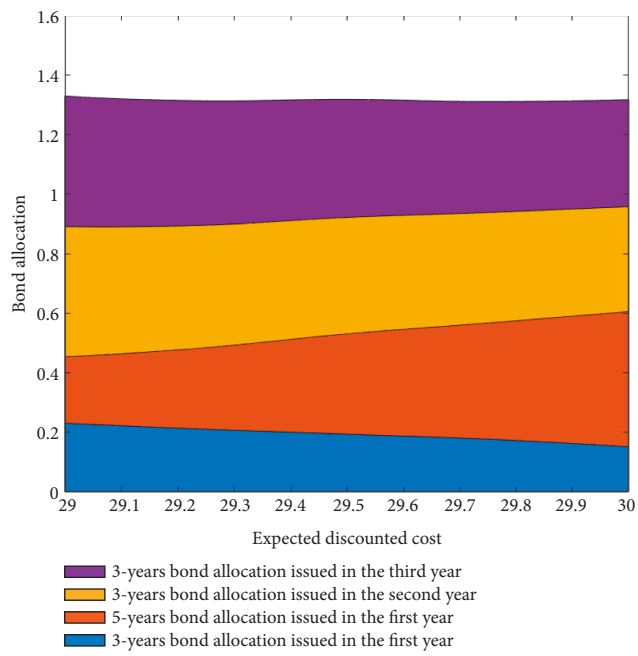


Figure 12: The total proportion of bonds that mature within the liquidity planning horizon **H** = 6 years under the fixed **CPaR** = 4 2.

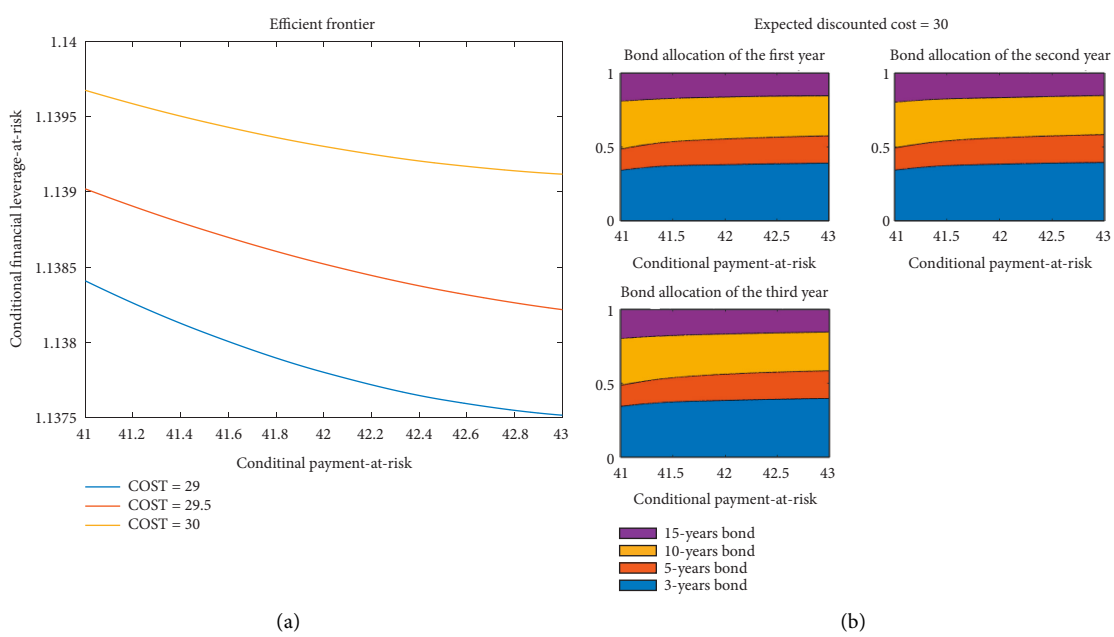


Figure 13: The efficient frontier curves of the minimum of **CFLaR** with the different **CPaR** and three fixed **COST** = 29, 29.5, 30 (a), the bond composition with **COST** = 30 and different **CPaR** (b).

Corresponding to a minimum *CFLaR* under fixed COST = 30, the optimal bond portfolio compositions for each year of the three-stage bond issuance planning horizon are shown in Figure 13(b). The bond portfolio includes all four types of bonds in each issuance year, and the proportions of 3-year and 5-year bond in each year in the three stages both increase as *CPaR* shifts from 41 to 43.

To further explore the evolution of the total payments of newly issued bonds when $H = 6$ years, we depict the total proportion of each kind of newly issued bond across the three stages in Figure 14. As shown in Figure 14, the total proportions of 3 years and 5 years bonds increase and the total proportions of 10 year and 15 year bonds gradually decrease across the three stages as *CPaR* shifts from 41 to 43. Additionally, Figure 14 shows that the total proportion curve for each newly issued bond becomes smooth as *CPaR* shifts from 41 to 43, i.e., the magnitude of the increase of the total proportions of 3 year and 5 year bonds gradually decreases and the magnitude of the decrease of the total proportion of 10 year and 15 year bonds gradually decreases. Thus, the rate

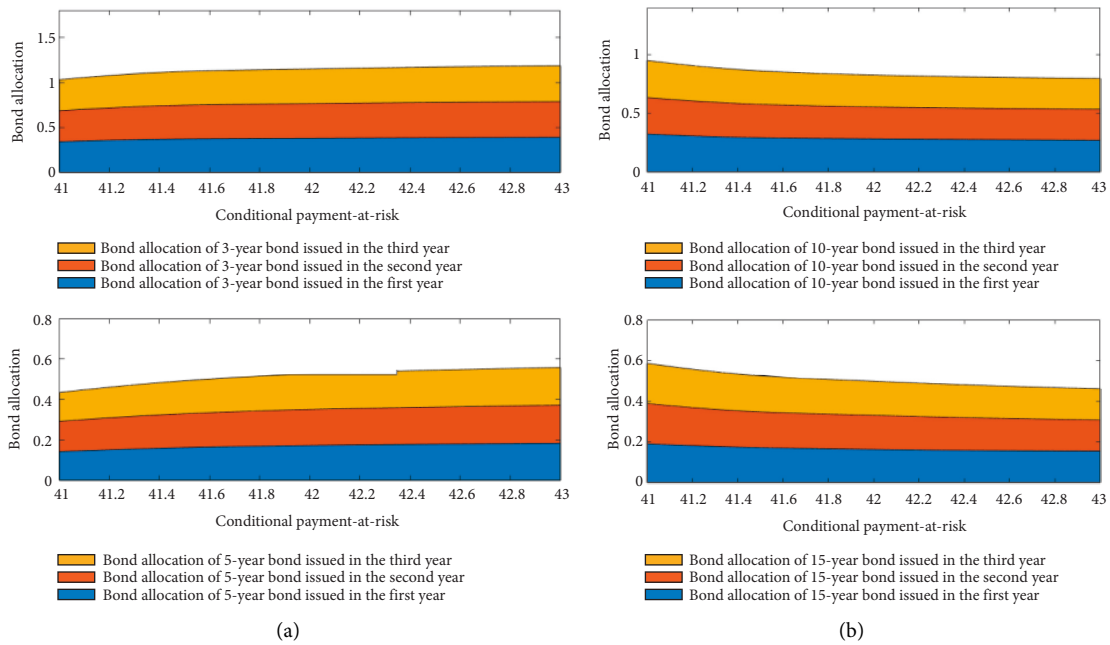


Figure 14: The total proportion of each kind of new issue that includes issued in the three stages as **CPaR shift** from 41 to 43.

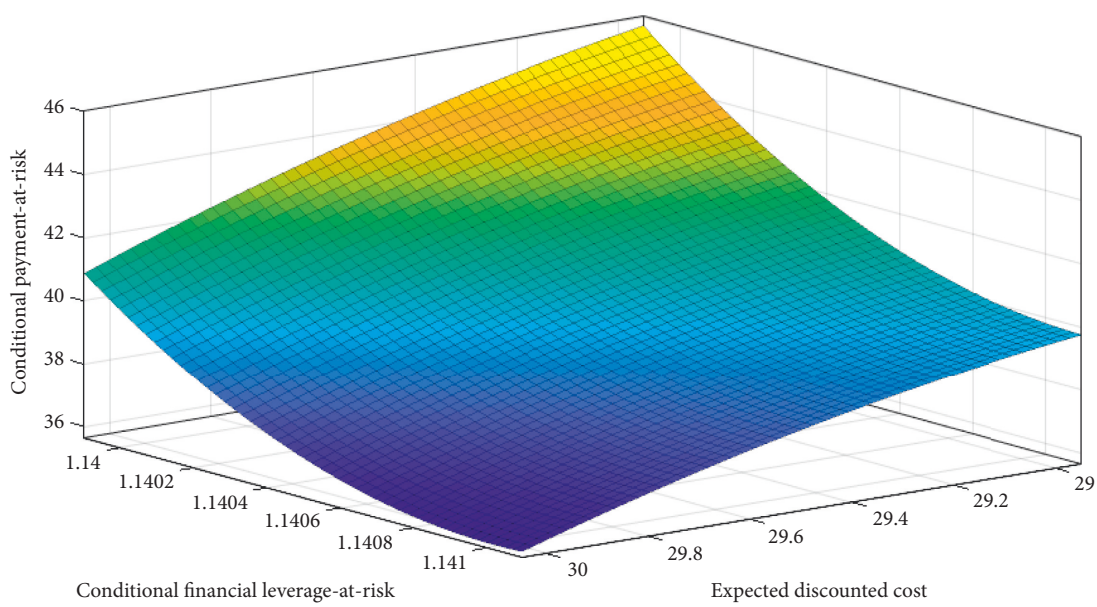


Figure 15: Efficient frontier of minimum of **CPaR** with different **CFLaR** and **COST** constraints.

of the decrease of minimum *CFLaR* gradually increases, as shown in Figure 13(a).

5.3.3. Case 3: Minimizing **CPaR** *under the Constraints of Different* **COST** *and* **CFLaR**. We provide the efficient frontier for minimum *CPaR* with the constraints of different $CFLaR \in [1.14, 1.141]$ and different $\text{COST} \in [29, 30]$ in Figure 15.

As shown in Figure 15, the minimum *CPaR* decreases as *CFLaR* increases and also decreases as COST increases. From Case I and Case II, we know that *CFLaR* is mainly determined by the interest payments of newly issued bonds and that COST is mainly determined by the total discounted payments of the principals of these newly issued bonds. Thus, an increase in the proportion of long-term bonds issued leads to an increase in COST and *CFLaR*; conversely, it leads to a decrease in minimum *CPaR*.

To explore the evolution of the efficient frontier more precisely, similar to our analyses for Cases 1 and *II*, we also consider the following two constraints.

(i) The efficient frontier curves of the minimal *CPaR* with the constraints of different *CFLaR* and three fixed COST.

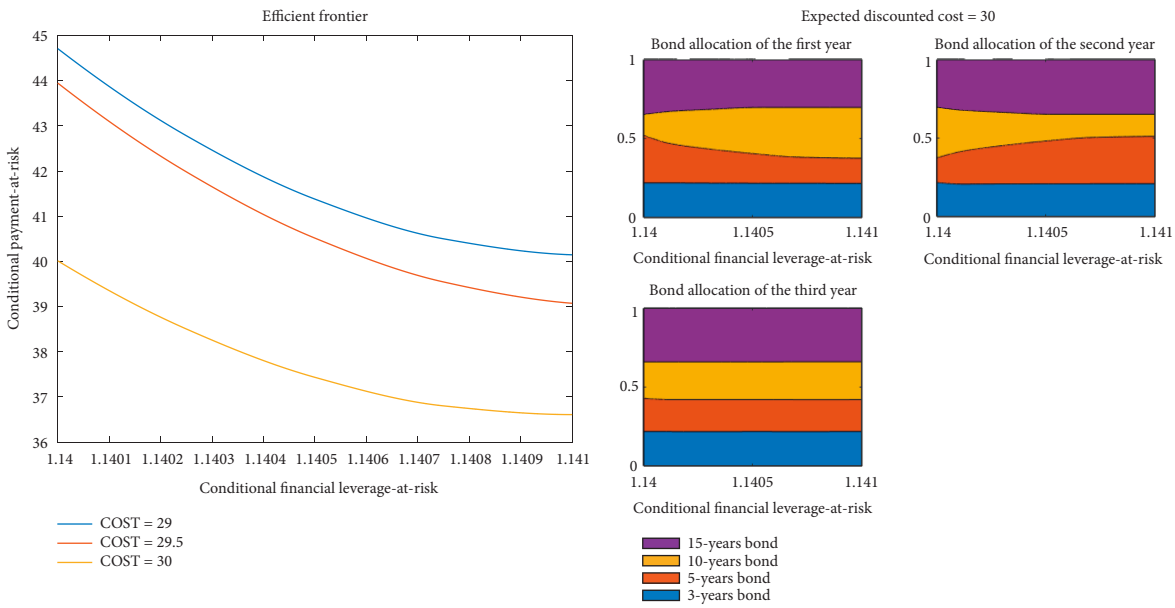


Figure 16: The efficient frontier curves of the minimum of **CPaR** under different **CFLaR** and three fixed **COST** = 29, 29.5, 30 (a), the bond composition with **COST** = 30 and different **CFLaR** (b).

The efficient frontier curves for minimum *CPaR* with the constraints of different *CFLaR* and three fixed COST. Figure 16(a) shows the corresponding efficient frontier curves for minimum *CPaR* under different *CFLaR* and three fixed COST = 29, 29.5, 30. As shown in Figure 16(a), each efficient frontier of minimum *CPaR* is a decreasing function of *CFLaR* for each fixed COST. An increase in *CFLaR* coincides with an increase in the proportion of long-term bonds, which leads to an increase in minimum *CPaR*, and vice versa. To further explore the optimal portfolio, we investigate an example with COST = 30 and provide the corresponding issuance of newly issued bonds within three stages in Figure 16(b).

Figure 16(b) shows the optimal bond allocation for each year of three-stage bond issuance with a 3-year planning horizon under the fixed COST = 30. To further examine the evolution of payment of newly issued bonds within $H = 6$ years, we use *Type I* bonds which method in Case 1, and give the total proportion of *Type I* bonds in Figure 17.

Because *CPaR* is determined by the total payments of *Type I* bond principals when $H = 6$ years and a bond's interest payments are a very small proportion of its principal, a decrease in *CPaR* requires the total payments of *Type* 1 bond principals during $H = 6$ years to decrease; that is, the total proportion of *Type I* bonds in the three stages must decrease. Figure 17 shows that the total proportion curve of the *Type I* bonds becomes smooth, which implies that as *CFLaR* shifts from 1.14 to 1.141, the magnitude of the decrease in the total proportion of *Type I* bonds gradually decreases. Thus, the magnitude of the reduction in *CPaR* gradually decreases; that is, the rate of decrease of minimum *CPaR* gradually falls, consistent with Figure 16(a).

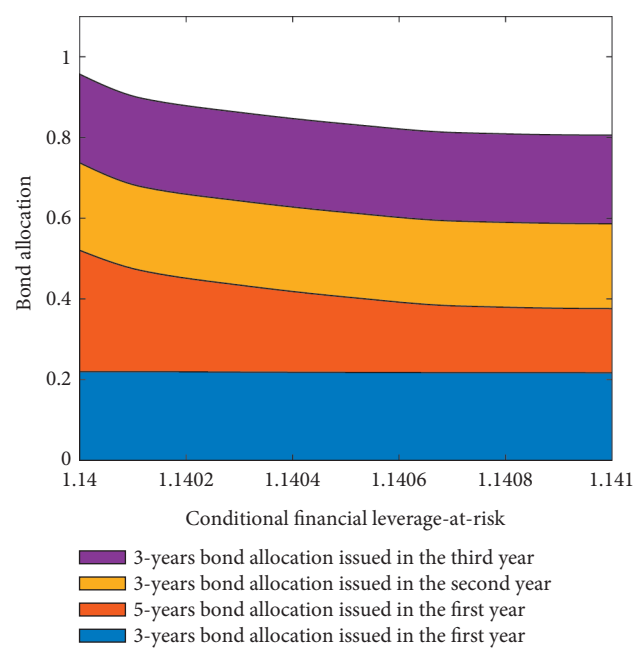


Figure 17: The total proportion of bonds that mature within the liquidity planning horizon **H** = *6* year under the fixed **COST** = 30.

(ii) The efficient frontier curves of the minimum of *CPaR* with the constraints of different COST and three fixed *CFLaR*.

The efficient frontier curves of minimum *CPaR* with the constraints of different COST and three fixed *CFLaR*.

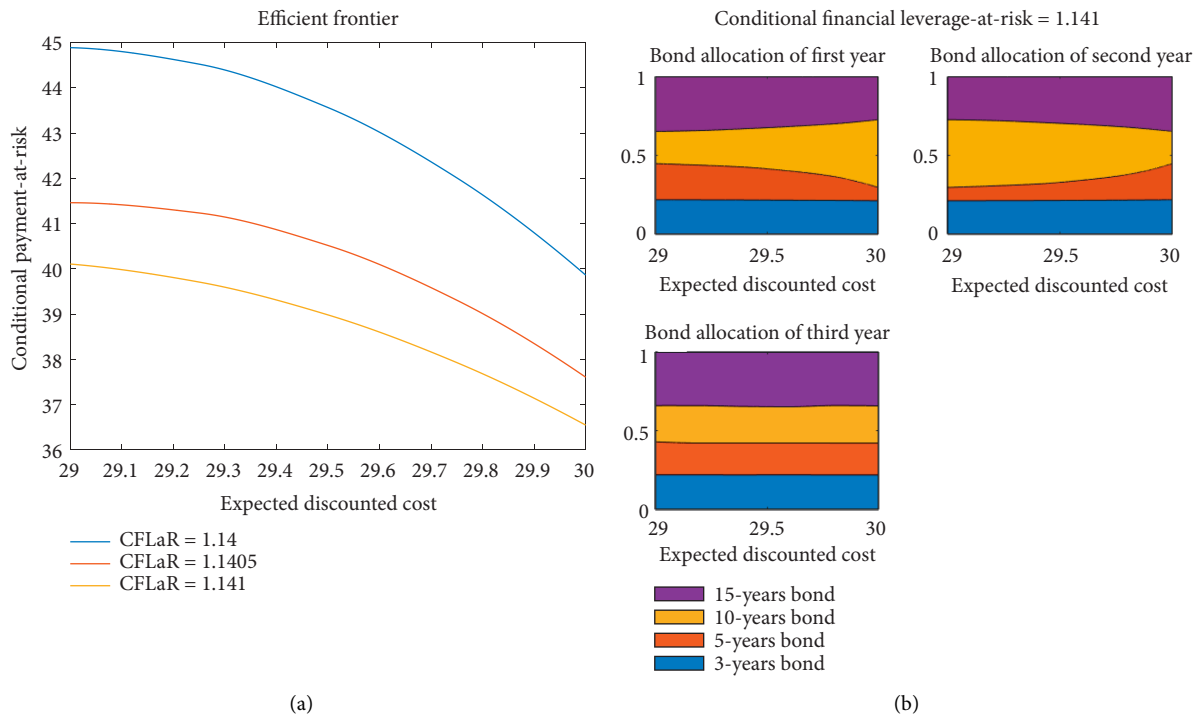


Figure 18: The efficient frontier curves of the minimum of **CPaR** under different **COST** and three fixed **CFLaR** = 1.14, 1.1405, 1.141 (a), the bond composition with **CFLaR** = 1.141 and different **COST** (b).

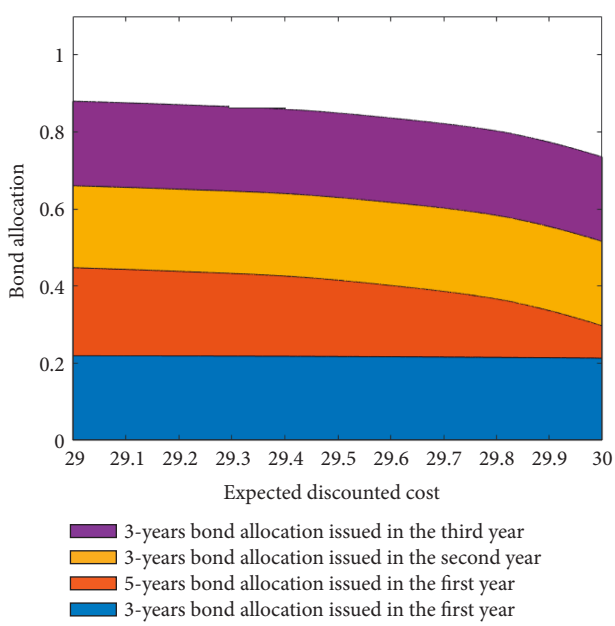


Figure 19: The total proportion of bonds that mature within the liquidity planning horizon **H** = *6* year under the fixed **CFLaR** = 1.141.

Figure 18(a) shows the corresponding efficient frontier curves for minimum *CPaR* under different COST and three fixed *CFLaR* = 1.14, 1.1405, 1.141. As shown in Figure 18(a), each efficient frontier of minimum *CPaR* is a decreasing function of COST under fixed *CFLaR* constraints. An increase in COST represents an increase in the proportion of long-term bonds, which leads to a decrease in minimum *CPaR*, with the order reversed. To further examine the optimal portfolio for minimum *CPaR*, we examine an example in which *CFLaR* = 1.141 and give the corresponding issuance allocation of newly issued bonds within the three stages in Figure 18(b).

Figure 18(b) shows the optimal bond allocation for each year of a three-stage bond issuance with a 3-year planning horizon under fixed *CFLaR* = 1.141. All four types of bonds are present in the bond allocation at each issuance stage, as shown in Figure 18(b).

We further explore the evolution of the minimum payments for the bonds issued within the three stages when $H = 6$ years, considering the proportion of *Type 1* bonds. As shown in Figure 19, the proportion of *Type I* bonds gradually decreases as COST shifts from 29 to 30, meaning that the minimum *CPaR* gradually decreases. Moreover, Figure 19 indicates that the total proportion curve of *Type I* bonds becomes steeper, which signifies that the magnitude of the decrease in the total proportion of *Type I* bonds gradually increases, and the magnitude of the decrease in *CPaR* gradually decreases when $H = 6$ years, i.e., the rate of decrease of the minimum *CPaR* gradually falls, which is consistent with Figure 18(a).

6. Conclusion

We propose an MSP model with multiple objectives to optimize bond issuance and design a *CFLaR* construct inspired by *CVaR* to measure financial leverage risk in worst-case scenarios. We further develop a corporate cash liquidity risk measurement construct, *CPaR*, that improves

on the existing liquidity risk measurement method. To help corporations achieve a trade-off between the expected discounted bond repayment cost and the two types of risks mentioned above, we discuss the following three cases: (1) minimizing *COST* under the constraints of different *CFLaR* and *CPaR*, (2) minimizing *CFLaR* under the constraints of different COST and *CPaR*, and (3) minimizing *CPaR* under the constraints of different *COST* and *CFLaR*.

We empirically test our model by applying it to a real Chinese company, ZOH. We assume that the company issues a bond portfolio comprising 3 years, 5 years, 10 years, and 15 years bonds within a three-year bond issuance plan period. Scenario trees simulating the evolution of macroeconomic variables are generated by HFS, and a three-stage stochastic programming bond issuance model is established for $H = 6$ years. Specifically, we examine the efficient frontier of minimum COST with different *CFLaR* and *CPaR* constraints, and the empirical results show that the minimum COST increases as *CFLaR* increases and decreases as *CPaR* increases. We provide the efficient frontier of minimum *CFLaR* with the constraints of different *CPaR* and different COST, which shows that minimum *CFLaR* increases with COST and decreases as *CPaR* increases. Finally, we consider the efficient frontier of minimum *CPaR* with the constraints of different *CFLaR* and different COST. The results show that the minimum *CPaR* decreases as COST increases and decreases as *CFLaR* increases.

The main contributions of this paper are as follows:

(i) We propose an MSP model with multiple objectives that optimize the uncertain bond issuance by satisfying the three common objectives of corporate managers: (i) minimizing the expected discounted cost under cash liquidity and financial leverage risk constraints; (ii) minimizing financial leverage risk under expected discounted cost and cash liquidity risk constraints; (iii) and minimizing cash liquidity risk under expected discounted cost and financial leverage risk constraints.

(ii) We improve on the *CPaR* method of measuring corporate short-term liquidity risk in a worst-case scenario of corporate bond issuance. Furthermore, based on the degree of financial leverage, we design a *CFLaR* construct to measure the financial leverage risk faced by a corporation in a worst-case scenario.

(iii) Through the empirical analysis of ZOH company, we show that corporations can adjust the proportion of short-term bonds maturing within the cash liquidity horizon to reduce the minimum expected discounted cost and minimum financial leverage risk in worst-case scenarios while fixing the level of short-term cash liquidity risk. When the financial leverage risk is fixed, corporations can change the proportions of the two types of newly issued bonds (maturing during and after the cash liquidity horizon) to achieve a trade-off between minimum expected discounted costs and minimum short-term cash liquidity risk in worst-case scenarios. By controlling the future repayment cost of bonds, corporations can modify the proportions of these two bond types to manage the minimum financial leverage risk and minimum short-term cash liquidity risk simultaneously in a worst-case scenario.

Our MSP model with multiple objectives considers the expected discounted cost of newly issued bonds, cash liquidity risk, and financial leverage risk in worst-case scenarios, providing guidance for corporations on devising effective management strategies for the issuance of corporate bonds. In future research, we will assign different weights to cost, liquidity risk, and financial leverage risk to establish more comprehensive and objective equations and constraints, allowing us to more accurately determine the corresponding optimal issuance strategy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Additional Points

Highlights. A multistage stochastic programming model with multiple objectives that optimizes the corporate bond issuance is proposed. In this paper, three common objectives of corporate managers are considered: (i) Minimizing expected discounted cost under cash liquidity and financial leverage risk constraints. (ii) Minimizing financial leverage risk under expected discounted cost and cash liquidity risk constraints. (iii) Minimizing cash liquidity risk under expected discounted cost and financial leverage risk constraints. Liquidity risk can be measured by conditional payment-at-risk (*CPaR*) model and financial leverage risk is captured by the conditional financial leverage-at-risk (*CFLaR*), which is based on conditional value-at-risk (*CVaR*). Corporations can adjust the proportions of the two types of newly issued bonds (maturing during and after the cash liquidity horizon) to reduce the minimum expected discounted cost, the minimum financial leverage risk in worst-case scenarios, and the minimum short-term cash liquidity risk in worst-case scenarios simultaneously.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Testing the Augmented Fama–French Six-Factor Asset Pricing Model with Momentum Factor for Borsa Istanbul

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This study aims to test the validity of the Fama–French Asset Pricing Model, which has become a six-factor along with the inclusion of the momentum factor, in terms of Borsa Istanbul. In this context, nested asset pricing models were assessed, and different estimators were developed to determine which of the models explains the stock returns more strongly. The returns (more than the risk-free interest rate) of 24 different portfolios and a total of 9,504 portfolios for 396 weeks, throughout October 2013–May 2021, are utilized based on the BV/MV, profitability, investment, and momentum factors. The results obtained from the research study indicate the Fama–French Six-Factor Asset Pricing Model (FF6F) as the most effective model in explaining stock returns for Borsa Istanbul. For investors, the momentum factor is the one that needs to be regarded and allows higher returns to be obtained, and the necessity of considering it before making investment decisions is one of the practical contributions of the research study. Determining the momentum factor as a factor that should be considered upon making investment decisions would constitute the contribution of the research study to the literature.

1. Introduction

Until the publication of Markowitz's article entitled "Portfolio Selection" in 1952, the comprehension that risk could be reduced by increasing the number of assets in portfolios was predominant in the markets. Nonetheless, in his related study, Markowitz [1] determined that even if the number of assets in the portfolio was increased with the modern portfolio approach, the portfolio risk would not have decreased if there was a high level of correlation among the assets. According to Markowitz [1], if the correlation among assets was low and negative, the portfolio risk would have been decreased. Following Markowitz's related study, Modigliani and Miller [2] made crucial contributions to the occurrence of normative literature regarding the development of corporate finance by investigating the relationships between firm value and capital structure. Besides these studies in the field of modern finance theory, Sharpe [3], Lintner [4], Mossin [5], and Black et al. [6] investigating the relationship between risk and return, as well as the SLM model, have constituted the landmarks in terms of finance literature.

The Capital Asset Pricing Model (CAPM) has been built on modern portfolio theory (MPT). The assumptions of the model regarding risk and returns are based on the assumptions of MPT, and the investor of the model is Markowitz's rational efficient investor. Various aspects of basic assumptions of the CAPM have been discussed, and criticism has been made that it is not possible to encounter the ideal market structure that it reveals. Criticism of the model has caused the assumptions to be altered. Following this situation, Ross [7] developed the arbitrage pricing model as an alternative to the CAPM. In the arbitrage pricing model, unlike the CAPM, evidence has been presented on the extent to which more than one variable would affect asset returns. Notwithstanding, the arbitrage pricing model, which was put forth as a critique of the CAPM, could not fully determine the factors affecting asset returns. In the following

years, the factors affecting asset prices began to be discussed frequently, and in recent years, the relevant literature has transformed the CAPM into multifactor models to explain the shift in asset prices.

Fama and French [8] were able to explain stock market anomalies in the 1980s employing the three-factor asset pricing model (FF3F) they developed, and the CAPM has become the basic model to explain the change in the cross-sectional asset returns [9].

The FF3F associates the cross-sectional change in stock returns with three elements as follows:

(i) The market return in excess of the risk-free interest rate

(ii) The difference between the portfolios of small and large companies in terms of returns

(iii) The difference between the portfolios of companies with high and low BV/MV ratios in terms of returns

In this context, the FF3F reveals that, unlike the CAPM, stock returns are affected not only by the market risk premium but also by the firm size as well as the BV/MV ratio. The shortcoming of the FF3F in explaining the changes in stock returns over time, the lack of the three factors of the model in fully capturing the variance of the average returns, and especially Titman et al. [10] and Novy [11] are the main motivation sources underlying the development of a brand new five-factor asset pricing model by Fama and French in 2015 [9, 12]. In this respect, Fama and French [12] developed the five-factor model (FF5F) by including profitability and investment variables in the three-factor model. There are various studies in the literature indicating that the FF5F performs better than the FF3F and the CAPM in explaining the variance in asset returns.

Nevertheless, the main problem of the FF5F involves the fact that small stocks, which tend to act as companies with high investment levels despite low profitability, cannot achieve average returns. Besides, the performance of the model is not sensitive to how the factors are described.

A remarkable FF5F study by Kubota and Takehara [13] suggested that the betas of the factors such as RMW (difference between stock returns of diversified stock portfolios with strong and weak profitabilities) and CMA (the difference between the returns of firms' diversified stock portfolios of companies with low and high investment levels, which are defined as conservative and aggressive), which are included in the FF5F for Japan, had weak relationships with the cross-section variances of the stock returns and yielded different results than the USA. In this respect, the results of the model tend to differ by country.

Fama and French [14] redeveloped the model by including the momentum factor into the FF5F to rank the asset pricing models and to maintain predictions regarding the maximum Sharpe ratio (Sh^2). The momentum factor (UMD, Up Minus Down) indicates the difference between the returns of the portfolio with higher market gearing and the returns of the portfolio with lower market gearing.

In this framework, the main motivation of the research is to test the validity of the Fama–French Six-Factor Asset Pricing Model (FF6F), which is one of the asset pricing models that developed in the historical process and became multifactor models along with the contributions of Fama and French for Turkey. Although FF3F and FF5F have been tested in Turkey so far, the absence of a study on the FF6F constitutes the original aspect of the research. In this context, the main purpose of the research is to investigate whether or not the momentum factor, which is newly added to the model, increases the power of explaining stock returns in Borsa Istanbul and to test the efficiency of the model within the Turkish market. The study contributes to the literature regarding the validity of the FF6F. Moreover, the results of the research study also contribute to investors, portfolio managers, portfolio management companies, and financial institutions, as they reveal the factors affecting portfolio selection on a country basis and test their efficiency.

In the next part of the research study, the literature review on multifactor asset pricing models is presented. The third part introduces the research methodology, the fourth part includes the findings, and the fifth part presents the conclusion and discussion part.

2. Literature Review

Over the last three decades, Sharpe's [3] and Lintner's [4] Capital Asset Pricing Model (CAPM) has been subjected to crucial criticism. Fama and French [8] expanded the CAPM along with size and value factors to render it more explanatory, and then a four-factor Carhart [15] model, including the momentum factor, was developed. Although both models have been frequently used in asset pricing studies on developed markets, it was observed that there were patterns such as profitability, asset growth impact, and accrual impact that these models could not grasp in stock returns [11, 16, 17]. In the next step, Fama and French [12] developed a five-factor model explaining the change in returns by including profitability and investment factors. A five-factor model that adds profitability and investment factors to the three-factor model of Fama and French [8] largely absorbs the patterns in average returns [18]. The five-factor model was tested for countries with developed stock markets, including North America, Europe, Japan, and the Asia Pacific, and it was concluded that the model was more successful in explaining the change in average returns. For instance, Lin [9] concluded that the five-factor model outperformed the three-factor model in the Chinese market over the period 1997 to 2015, whereas the important investment factor was redundant. Huang [19], in compliance with the results of Lin [9], determined that the five-factor model was superior to other asset pricing models in the Chinese market over the period 1994–2016. Leite et al. [20] investigated the Fama–French three-factor, four-factor, and five-factor models for developing countries. The results of the research study indicated that the four-factor and five-factor models outperformed the three-factor model. The value factor seemed unnecessary in the presence of profitability and investment factors, and the size factor was effective in average stock returns. In his research study on 18 different developing countries, Foye

[21] concluded that the five-factor model outperformed the three-factor model. Nonetheless, profitability and investment premiums were not distinguishing enough for Asia. Cox and Britten [22] asserted that the five-factor model best explained the cross-sectional returns in the Johannesburg stock market, and the profitability factor was more consistent than the investment factor. Ali et al. [23] tested the Fama and French three-factor, five-factor, and six-factor and Carhart's four-factor models for the Pakistan stock market over the period 2003–2016 and concluded that the Fama and French five-factor model explained the abnormal change in returns better than other models. At the same time, according to the research study, the profitability factor was effective in explaining the average returns. According to Mosoeu and Kodongo [24], the profitability factor was effective in explaining stock returns in countries such as Australia, China, and South Africa; however, research studies conducted in the American and Japanese markets differed. Guo et al. [25] detected that the factors of size, value, and profitability had strong impacts in explaining the average returns for the Chinese stock market; however, they concluded that the investment factor had a weak impact. Zaremba et al. [26] tested the Capital Asset Pricing Model, Fama and French three-factor asset pricing model, Carhart's four-factor asset pricing model, and Fama and French five-factor asset pricing model over the period 2000–2018 for Poland, which was categorized as a developing country. According to the results of the research study, the four-factor model performed better than the other models. In their research study, conducted on the Japanese market over the period 1978–2014 employing the GMM method, Kubota and Takehara [13] concluded that the Fama and French five-factor asset pricing model was not the best pricing model. Azimli [27] tested the five-factor model and three other models for Borsa Istanbul. The results indicated that only beta and book/market impacts were significant, whereas later included profitability and investment factors did not increase pricing or economic performance. The results asserted that different models yielded better results in different markets. Horváth and Wang [28] investigated Fama and French's five-factor model during COVID-19. The results revealed that the Dotcom bubble has a statistically significant impact on the R^2 of the growth model. Furthermore, in 2008, R^2 of growth portfolios was shown to be lower. Additionally, R^2 increased significantly due to the recent COVID-19. Furthermore, in the GMM model, beta model parameters were shown to be insignificant.

Subsequently, Fama and French [14] extended the five-factor asset pricing model by including the momentum factor. The momentum factor was denoted by UMD_t (up minus down) in the model. In the extended model with the momentum factor, the UMD was defined the same as the HML; however, it had been updated monthly instead of annually. UMD denoted the average value of UMD_s and UMD_b. The results indicated that the six-factor model outperformed the nested models, such as CAPM, three-factor, and five-factor models. Besides, it was concluded that the momentum factor could better explain Sh^2 (f). On the other hand, Ali and Ülkü [29] and Fama and French [14] determined that the expected returns in the six-factor model could not explain the mispricing factor, undervalued minus overvalued (UMO), and quality minus junk (QMJ) premiums. Procedures that were suggested by various factor spanning tests as well as Barillas and Shanken [30] and Barillas et al. [31], which comprise the market, UMO, and momentum factors, often outperform the six-factor model. Ali [32] tested the UMO (undervalued minus overvalued) proposed by Hirsleifer and Jiang [33] in the Pakistan stock market for the first time. The results determined that the UMO factor was significant for the long-term low-priced and short-term high-priced stocks, and it gained risk-adjusted returns. Moreover, upon analyzing the UMO factor with other asset pricing models (CAPM, Carhart's four-factor, and Fama and French three-, five-, and six-factor models), it revealed information that could not be identified by other factors in the Pakistani stock market. Ali [32] concluded that the four-factor model comprising UMO, size, and profitability factors would have performed better in his study using factor spanning regression, Barillas and Shanken's [30] maximum Sharpe square ratio, and GRS test metrics over the period 2003–2018.

In another striking study, Dirkx and Peter [34] conducted a research on the German market employing the Fama–French six-factor model obtained by including the momentum factor to the Fama–French three-and five-factor asset pricing models. The monthly data obtained over the period 2002–2019 were used in the empirical research. The number of factors used in the study, as used in the Fama–French five-factor asset pricing model, became six by including the momentum factor besides market factor, size factor, value factor, profitability factor, and investment factor. According to the preliminary analysis results of the research study, no significant finding was obtained in terms of profitability and investment factors. Upon comparing the results of the six-factor model with the results of the three-factor model, the included factors do not make a significant contribution to the analysis in terms of explanatory power. As a result of the research, it was concluded that the use of profitability and investment factors in the context of international asset pricing studies did not have a statistically significant contribution to explaining the stock returns in the German stock market.

3. Methodology

The main purpose of the research study is to test the validity of the FF6F in terms of Borsa Istanbul. Within the scope of the study, the returns of 24 different portfolios exceeding the risk-free interest rate are utilized along with the weekly obtained data (396 weeks) over the period October 2013–May 2021 based on value, investment, profitability, and momentum factors. A total of 9,504 portfolios (24 portfolios $*$ 396 weeks) are generated in the study. In the study, estimators are developed by employing the FF3F, the FF4F, the FF5F, and the FF6F separately to determine which of these models would better explain stock returns in Borsa Istanbul. Although the monthly or annual data are usually used in asset pricing models, the weekly data are used in this research study. Black [35] stated that many asset pricing models utilized the realized returns that did not accurately

reflect expected returns to test the hypotheses. Nevertheless, Liu et al. [36] asserted that assets should have acted together in an efficient market, and therefore, expected returns in shorter prediction intervals were closer to the actual returns. It was the main reason why the weekly data were preferred in the research study.

The weekly returns of the Borsa Istanbul National 100 Index are taken as the basis for market returns. For the weekly returns, the closing data obtained over the period 2013–2021 are utilized. The rate of return of the market factor at week t is calculated by dividing the market's weekend t value by the previous weekend's value and by taking its natural logarithm. The data of the "Average Cost of Domestic Borrowing" table were converted into weekly data and used as the risk-free interest rate. The relevant data are obtained from the official website of the Turkish Republic Ministry of Treasury and Finance (https://www.hmb.gov.tr/). The weekly return of the stock and the weekly return of the BIST National-100 index used in the study is obtained from the Finnet Electronic software.

In the study, Fama–French's [12] sampling criteria are used. They include all companies (except for financial sector companies) which traded in Borsa Istanbul over the period between October 2013 and May 2021. Besides, companies with high leverage and negative equity are excluded from the sample.

The market values of the firms are used for the size factor. The companies are ranked separately for each year t according to their market values as Fama and French [12] did in their study. In the study, the value factor companies, which are categorized into two groups as small and big, considering the size of the company, are independently ranked from small to large according to the book value/market value ratio and are divided into 3 groups, and this process is repeated for each year t by the methodology of Fama and French [12]. The profitability factor is considered the operating profitability ratio and is calculated by dividing the operating profit of the company by the book value of equity. Following the methodology of Fama and French [12], companies that are divided into two groups, small and big, are divided into three groups, R, M, and W, according to their profitability ratios. The investment rate is calculated by dividing the difference between the total value of assets in years $t-1$ and $t-2$ by the total value of assets in year $t-2$ and is similarly classified into three groups. It is determined as 30% for the group with low-level cut-offs in all factors, 40% for the group with intermediate level, and 30% for the group with a high level.

Employing the FF3F, the β coefficient related to the market sensitivity in the CAPM is excluded from the model, and instead, the value and size factors are included in the model with the assumption that it better handles the cross-sectional change. Fama and French developed the current model by including the investment and profitability factors into the FF3F in 2015 since the FF3F was insufficient to explain some anomalies and cross-sectional variation in expected returns associated with investment and profitability. As such, the new model is known in the literature as the FF5F [13]. The FF5F, which was developed since the FF3F was insufficient to explain the expected return, would be formulated as follows [37]:

$$R_{it} - R_f = a_i + \left(R_{Mt} - R_{ft}\right) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_i. \tag{1}$$

In the FF5F, besides the stock return, the systematic risk premium β_i (RM-RF), market factor, value factor (HML), size factor (SMB), investment factor (CMA), and profitability factor (RMW) variables are utilized. Fama and French [14] tested the validity of the obtained six-factor model by including the momentum variable into the FF5F in terms of the US stock markets. Following this study, Dirkx and Peter [34] conducted a similar research study in terms of the German stock market. In this respect, the validity of the FF6F would be employed in terms of Borsa Istanbul by taking the aforementioned research studies as a reference. The momentum variable is utilized as the sixth factor in this research study, similar to the studies of Fama and French [14] and Dirkx and Peter [34]. In the study, the impacts of the 6 explanatory variables shown below on the return of 24 portfolios are examined.

$$R_{it} - R_{ft} = \alpha_i + b_i\left[R_{mt} - R_{ft}\right] + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + m_i MOM_t + \varepsilon_i. \tag{2}$$

The factors used in the research study express the changes in the returns of the companies and the change in the price of the stocks in each portfolio concerning the previous periods.

$[R_{mt} - R_{ft}]$ is the market risk premium return change.

SMB_t is the change in returns of portfolios generated according to firm size.

HML_t is the change in returns of portfolios generated according to book/market values ratio.

CMA_t is the change in returns of portfolios generated according to investment changes.

$RMW_t$is the change in returns of portfolios generated according to the operational profitability of the company.

MOM_t is the momentum factor referring to winners and losers. Therefore, momentum factor is based on past winners (W), neutral performers (N), and losers (L) [34].

(i) Market risk premium is the market return (BIST100) – risk-free interest rate.

(ii) $SMB$is the difference between returns on small and large-cap stocks

$$= \frac{(SL + SM + SH)}{3} - \frac{(BL + BM + BH)}{3}. \tag{3}$$

(iii) $HML$is the difference between returns on stocks with high and low BV/MV ratios

$$= \frac{(SH + BH)}{2} - \frac{(SL + BL)}{2}. \tag{4}$$

(iv) RMW is the difference between returns on stocks with high and low profitabilities

Table 1: Portfolios used in the study.

Portfolio	Firm size	Value effect	
SL[2]	Small	Low	**Book value/market value**
SN	Small	Neutral	
SH	Small	High	
BL	Big	Low	
BN	Big	Neutral	
BH	Big	High	
SC	Small	Conservative	**Investment**
SM	Small	Medium	
SA	Small	Aggressive	
BC	Big	Conservative	
BM	Big	Medium	
BA	Big	Aggressive	
SW	Small	Weak	**Profitability**
SM-	Small	Medium	
SR	Small	Robust	
BW	Big	Weak	
BM-	Big	Medium	
BR	Big	Robust	
SC	Small	Conservative	**Momentum**
SN	Small	Neutral	
SA	Small	Aggressive	
BW	Big	Past winners	
BN	Big	Neutral performers	
BL	Big	Losers	

[2]It denotes the return on a portfolio of stocks with small company size and low book value/market ratio.

$$= \frac{(SR + BR)}{2} - \frac{(SW + BW)}{2}. \quad (5)$$

(v) *CMA* is the difference between returns on stocks with high and low investments

$$= \frac{(SC + BC)}{2} - \frac{(SA + BA)}{2}. \quad (6)$$

(vi) *MOM* is the based on past winners (*W*), neutral performers (*N*), and losers (*L*), $\mathrm{MOM_t}$ is derived as

$$= \frac{(SW + BW)}{2} - \frac{(SL + BL)}{2}. \quad (7)$$

Since there are fewer financial assets in Borsa Istanbul compared to the US market, a correction is made by calculating 24 weighted portfolios instead of 25 (5×5). A similar correction was also made regarding the portfolio diversification in the research study conducted by Dirkx and Peter [34] on the German Stock Exchange.

Table 1 presents the portfolios utilized in the study. After the companies are categorized into 2 groups, such as large and small scale, while creating portfolios, portfolios are categorized into 4 groups, namely, "market value/book value," "investment," "profitability," and "momentum." Two distinct portfolios, such as "small (Small-S)" and "large (Big-B)," are generated regarding the size effect. Three distinct portfolios, such as "high (Big-B)," "neutral (Neutral-N)," and "Low-L," are selected according to market value/book value regarding the value effect. Then, 6 value-weighted portfolios are generated (2×3) with the intersections of portfolio composition according to size and market value/book value. Within the scope of the study, consistent with Fama and French [14], the following models are developed to cover the aim of the study and the generated portfolios:

$$\begin{aligned}
R_{it} - R_{ft} &= \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + \varepsilon_i, \\
R_{it} - R_{ft} &= \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i\left(SMB_t\right) \\
&\quad + h_i\left(HML_t\right) + \varepsilon_i, \\
R_{it} - R_{ft} &= \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i\left(SMB_t\right) \\
&\quad + h_i\left(HML_t\right) + r_i\left(RMW_t\right) + \varepsilon_i, \\
R_{it} - R_{ft} &= \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i\left(SMB_t\right) \\
&\quad + h_i\left(HML_t\right) + r_i\left(RMW_t\right) + c_i\left(CMA_t\right) + \varepsilon_i, \\
R_{it} - R_{ft} &= \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i\left(SMB_t\right) \\
&\quad + h_i\left(HML_t\right) + r_i\left(RMW_t\right) \\
&\quad + c_i\left(CMA_t\right) + m_i\left(MOM_t\right) + \varepsilon_i.
\end{aligned} \quad (8)$$

In this context, the hypotheses of the GRS-F test are as follows [38]:

H_0: all alpha coefficients obtained from the CAPM, Fama–French three-, four-, five-, and six-factor models are equal to zero ($\alpha_i = 0$).

Table 2: Descriptive statistics for intersection portfolios exceeding the risk-free interest rate.

	N (weeks)	Mean	Std. dev
SL	396	0.0021	0.03356
SN	396	0.0025	0.02977
SH	396	0.0015	0.02922
BL	396	0.0016	0.02431
BN	396	0.0032	0.02370
BH	396	0.0011	0.02695
SC	396	0.0025	0.03067
SM	396	0.0021	0.03019
SA	396	0.0007	0.03003
BC	396	0.0022	0.02701
BM	396	0.0020	0.02460
BA	396	0.0026	0.02695
SW	396	0.0007	0.02978
SM-	396	0.0019	0.02877
SR	396	0.0042	0.03169
BW	396	−0.0008	0.02836
BM-	396	0.0025	0.02419
BR	396	0.0034	0.02342
SC-	396	0.0018	0.02752
SN-	396	0.0024	0.03195
SA-	396	0.0016	0.03454
BW-	396	0.0019	0.02754
BN-	396	0.0033	0.02532
BL-	396	0.0012	0.02432

H_1: all alpha coefficients obtained from the CAPM, Fama–French three-, four-, five-, and six-factor models are not equal to zero ($\alpha_i \neq 0$).

It is a statistic proposed by Gibbons et al. [38] to test the future effectiveness of the asset portfolio under examination. It is designed to test the effectiveness of the CAPM model and the portfolio on a mean-variance basis. With the GRS test, it can be tested whether or not the fixed terms calculated as a result of the regression equation in the asset pricing model are equal to zero for all stocks or portfolios. The null hypothesis of the test implies that the constant term of the entire stock or portfolio examined by the model is equal to zero (39). Gibbons et al. [38] expressed the statistics with different parameters as follows:

$$GRS = \left(\frac{T}{N}\right)\left(\frac{T}{T}\frac{-N-L}{-L-1}\right)\left[\frac{\widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\alpha}}{1+\overline{\mu}\prime\widehat{\Omega}^{-1}\overline{\mu}}\right]$$

$$\sim F(N, T-N-L),$$

$$\widehat{\alpha} = Nx1 \text{ estimated constant term vector,} \quad (9)$$

$$\widehat{\Sigma} = \text{error terms unbiased covariance matrix,}$$

$$\overline{\mu} = Lx1 \text{ factor portfolio mean matrix,}$$

$$\widehat{\Omega} = \text{Factor portfolio unbiased covariance matrix.}$$

T is the denotes the number of observations, N denotes the number of regression equations, and L denotes the number of factors in the regression.

Table 3: Unit root test results.

Variables	LLC test		PP Fisher test	
	t-test	Probability (p)	Statistic	Probability (p)
SL	−8.45	0.000	42.43	0.000
SN	−9.45	0.000	65.64	0.000
SH	−14.84	0.000	67.50	0.000
BL	−9.75	0.000	55.82	0.000
BN	−23.95	0.000	81.73	0.000
BH	−12.50	0.000	75.78	0.000
SC	−8.55	0.000	53.71	0.000
SM	−9.85	0.000	97.53	0.000
SA	−12.64	0.000	107.27	0.000
BC	−12.64	0.000	53.29	0.000
BM	−13.54	0.000	88.38	0.000
BA	−22.63	0.000	76.34	0.000
SW	−14.63	0.000	69.61	0.000
SM-	−12.44	0.000	123.45	0.000
SR	−14.97	0.000	53.93	0.000
BW	−16.64	0.000	87.30	0.000
BM-	−9.64	0.000	75.38	0.000
BR	−16.02	0.000	87.38	0.000
SC-	−7.63	0.000	56.88	0.000
SN-	−9.53	0.000	89.32	0.000
SA-	−12.73	0.000	98.54	0.000
BW-	−19.42	0.000	43.50	0.000
BN-	−13.63	0.000	68.39	0.000
BL-	−14.32	0.000	64.22	0.000
RM-RF	−15.89	0.000	77.52	0.000
SMB	−12.34	0.000	87.65	0.000
HML	−15.34	0.000	87.54	0.000
CMA	−20.33	0.000	93.34	0.000
RMW	−9.54	0.000	33.43	0.000

$H_0: \alpha_i = 0$ i: 1,2,3, . . ., N.
$H_1: \alpha_i \neq 0$ i: 1,2,3, . . ., N.

4. Findings

In this part of the study, the validity of the FF6F is tested for Turkey.

Descriptive statistics regarding the generated portfolios in the research study are presented in Table 2. The BN portfolio, which is comprised of stocks with a small to medium BV/MV ratio in terms of value-weighted weekly return and firm size, has the highest mean value. The SR portfolio with small firm size and high-yielding stocks has the highest weekly return.

The hypotheses regarding the unit root tests of the variables are as follows:

H_0: an overall unit root exists in the series (H_0: $p_i = p = 1$).

H_1: no overall unit root exists in the series ($H_0 = p_i = p < 1$).

The ability to perform econometric analyses on the variables used in the study depends solely on the fact that the series is stationary; in other words, they do not contain unit roots. If the variables exhibit a trend, the relationship involves a spurious regression rather than an actual one [40].

Table 4: Correlation analysis of factor premiums.

	RM-RF	SMB	HML	CMA	RMW	MOM
RM-RF	1					
SMB	0.097	1				
HML	0.095	−0.264	1			
CMA	0.136	0.017	0.179	1		
RMW	0.012	0.139	−0.075	−0.036	1	
MOM	0.041	−0.162	0.297	0.014	0.027	1

Table 5: Estimator results.

$R_i - R_f$	A	β	S	H	R	c	M	GRS-F	DW	F-statistic	Adj. R^2
CAPM	0.026 (0.276)	0.304 (3.102)**	—	—	—	—	—	1.68 (0.11)	2.093	27.53 (0.000)	0.321
FF3F	0.012 (0.183)	0.298 (3.041)**	0.565 (4.343)**	0.164 (1.856)*	—	—	—	1.54 (0.19)	1.753	29.32 (0.000)	0.362
FF4F	0.002 (0.143)	0.322 (3.264)**	0.464 (3.974)**	0.175 (1.904)*	.545 (4.565)**	—	—	1.29 (0.28)	2.031	31.76 (0.000)	0.385
FF5F	0.017 (0.206)	0.215 (2.343)**	0.653 (5.623)**	.202 (2.005)*	.492 (3.875)**	.503 (3.943)**	—	1.12 (0.38)	2.129	35.97 (0.000)	0.402
FF6F	0.021 (0.232)	0.301 (3.094)**	0.527 (4.242)**	0.194 (1.988)*	.405 (3.215)**	.551 (4.640)**	.364 (3.574)**	1.10 (0.39)	1.875	38.01 (0.000)	0.427

Table 6: Testing equality of squared Sharpe ratios for competing models.

	Differences in sample squared Sharpe ratios			
Models	2	3	4	5
1	0.094**	0.098**	0.105**	0.126**
2		0.084*	0.091**	0.119**
3			0.082*	0.112**
4				0.103*

* and ** indicate significance at the 5% and 1% levels, respectively.

Table 3 presents the unit root test results calculated by the LLC and PP Fisher tests. Both test results indicate that the variables are stationary and do not contain unit roots. Since the series are stationary, the null hypothesis (H_0), which implies that the variables contain unit roots, is statistically rejected.

Table 4 presents the correlation analysis results regarding factor premiums. Analysis results indicate that a positive relationship exists between the change in the return of RM-RF market risk premium and SMB, HML, and CMA variables. Similarly, although statistically weak, RM-RF is positively correlated with RMW and MOM variables. Upon examining the relationship between independent variables, it is understood that an inverse relationship exists between SMB and HML factors, whereas CMA and HML factors are positively related. It is seen that there are quite low correlations among the independent variables utilized in the study. It can be claimed that this situation may mitigate multicollinearity problems and spurious regression results that may arise in the model.

Table 5 indicates the regression results for all related models. Upon examining the analysis results, it is understood that the 5 models developed with 24 portfolios are significant, and there is no autocorrelation. The R^2 values of the CAPM, FF3F, FF4F, FF5F, and FF6F are 32.1%, 36.2%, 38.5%, 40.2%, and 42.7%, respectively. It indicates that the FF6F has the highest explanatory power in explaining stock returns.

Nevertheless, the alpha coefficients are equal to zero, and no pricing error exists in the developed models. Besides, the market factor β coefficients are positive and significant in the models. The value factor "h" coefficient is statistically significant. Similarly, the profitability factor "r" coefficient is positive and significant. Consequently, the coefficient of investment factor "c" is statistically significant. The momentum variable "m" is seen to be statistically significant in the FF6F regression model.

As a result, the H_0 hypothesis is accepted for the CAPM, FF3F, FF4F, FF5F, and FF6F according to the GRS-F test results. In other words, it is determined that the CAPM, FF3F, FF4F, FF5F, and FF6F are valid for Borsa Istanbul since there are no pricing errors in the models.

Table 6 presents the pairwise tests of equality of the squared Sharpe ratios of the 5 models within the framework

of Barillas et al. [31]. This table expresses the difference between the $\theta 2_i - \theta 2_j$ sample square Sharpe ratios indicated in column i and row j of the models developed in the research study. Barillas et al. [31] metric and covering non-nested models are used for generalization. These models express a superior model of higher $\theta 2$ in comparison. According to the analysis results, it is understood that, at the 1% significance level, Model 1 performs lower than all other models ($p < 0.05$). Nonetheless, Model 4 outperforms Model 3, Model 2, and Model 1. Also, Model 3 performs higher than Model 2 and Model 1 ($p < 0.01$). Model 5, however, statistically significantly performs higher than all other models. Consequently, it is understood that the best model developed in the research study is the 5-factor momentum model ($R_m - R_{ft}$, *SMB, HML, RMW, CMA,* and MOM_t).

5. Conclusion

The main objective of this research study is to test the validity of the Fama and French six-factor model for Borsa Istanbul. Turkey is categorized as a developing country, and the importance of emerging markets is increasing day by day. However, there is a limited number of studies that explain the change in returns in emerging stock markets employing multifactor asset pricing models. To fill this gap, the CAPM, Fama and French [8] three-factor model, Fama and French four-factor model, Fama and French [12] five-factor model, and Fama and French [14] six-factor models are tested using 396-week data obtained over the period October 2013–May 2021 by creating 24 different portfolios in Borsa Istanbul. To increase the reliability of the models, the GRS-F test is also performed with the adjusted resistive estimator employing the Newey-West method.

The empirical results of the research study indicate that the Fama and French [14] six-factor model outperforms other multifactor asset pricing models for Borsa Istanbul. There is no pricing error in the models developed in the research study. Accordingly, the results are similar to those of Fama and French [14] in terms of US stock markets. Fama and French [14] concluded that the six-factor model could better explain stock returns in the US market. Nonetheless, multifactor models do not yield similar results for all countries and financial markets. Although the obtained results of this research study for Borsa Istanbul indicate that the Fama and French [8] three-factor model, the Fama and French four-factor model, the Fama and French [12] five-factor model, and the Fama and French [14] six-factor model explain the variation of stock returns more strongly, Dirkx and Peter [34] concluded that became a five-factor model by the inclusion of the investment and profitability variables in the three-factor model for the German Stock Exchange and lastly included that the momentum factor did not increase the explanatory power of the model. The specific differences that financial markets exhibit by country may account for different results obtained from the German Stock Exchange. Moreover, the fact that the results of the research study do not comply with the results of Ali and Ülkü [29] accounts for the validity of the six-factor model varying by country in terms of its power to explain different factor premiums. Ali and Ülkü [29], contrary to our research findings, stated that the three-factor model, which consists of the market, UMO, and momentum factors, often outperformed the six-factor model.

The β coefficient is found to be positive and significant in the models tested in the study. At the same time, book-to-market value is considered an important factor. In this context, the results comply with the results of Azimli [27], which tested the five-factor model for Borsa Istanbul. Accordingly, in studies that tested asset pricing models for emerging markets, it is seen that, in general, new factors included in the model are more successful in explaining the change in stock returns [9, 19–21]. Nevertheless, since countries have financial markets with different characteristics, it should not be overlooked that all of the newly included factors in the model may not always explain the change in returns to the same degree.

At this point, Fama and French [14] attract attention to a crucial point. Accordingly, the increasing demand for the inclusion of empirically sound factors lacking theoretical motivation to the model, as well as the accompanying parsimonious models, may hamper the entire model.

The results of this research study are crucial for academics, investors, portfolio managers, and policymakers. The research study is the first to test the Fama and French [14] six-factor model for Borsa Istanbul. Within the scope of Borsa Istanbul, portfolio managers should take into account the momentum factor to ensure a stronger portfolio performance, whereas policymakers should consider the momentum factor to make effective decisions regarding risk and return factors.

The number of empirical studies on the six-factor model is still limited. Future studies to be conducted on different country groups and their probable findings would help us to have a clearer view of multifactor asset pricing models.

Data Availability

The data used to support the findings of this study are obtained from the Borsa Istanbul Databank.

Disclosure

This research was presented as a paper at the 24th Finance Symposium held in Sakarya, Turkey, on October 20–23, 2021, and was later developed and expanded.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Ownership, Corporate Governance, and Bank Performance in Iran

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An efficient banking system with the right monetary policy by controlling liquidity and inflation and directing resources to productive economic activities plays an essential role in economic development. However, banks' performance is influenced by various political, economic, managerial, and social factors, and the study of these factors has been considered the topic of interest to researchers. This paper uses the structural equation modeling method to investigate the effect of ownership structure and corporate governance on listed banks' performance in the Tehran Stock Exchange from 2011 to 2017. Based on the results, ownership structure dimensions have a relatively insignificant impact on corporate governance. However, the financial performance dimension has a statistically significant negative effect. The results also indicate that corporate governance is significantly associated with a positive effect on financial performance. Consequently, the results indicate that corporate governance may mitigate the negative impact that ownership structure dimensions may have on bank financial performance.

1. Introduction

Nowadays, the banking system's performance, especially in the optimal allocation of resources under the direct influence of investment, ensures the country's prosperity of production, employment, and economic growth. In other words, since improving the performance of banks and financial institutions in a country can improve the country's economic situation, it is necessary to study the conditions that improve the performance of banks and financial institutions [1]. On the other hand, banks operate in a unique public oversight environment and banking rules and regulations. The framework of corporate governance framework is much more complex than other companies. Corporate governance mechanisms reduce agency problems in companies, and the quality of these mechanisms is relative and varies from company to company, affecting different performance aspects. The issue of corporate governance in banks depends on managers' characteristics, the composition of board members and financial incentives, and other incentives to align critical players' activities with shareholders' interests. Senior executives may be selected among the major shareholders or a nonshareholder hired. Most bank managers are initially selected among the shareholders, but if the shareholders do not have enough experience managing banking operations, hiring professional managers is on the agenda. Professional managers are experts needed to manage the bank's operations properly. Still, these managers may not necessarily be incentivized to maximize shareholder wealth for various reasons, including how they are selected and appointed. The hired manager's behavior may not necessarily be in the interests of shareholders [2].

Using structural equation modeling, this study investigates the relationship between ownership structure and corporate governance mechanisms with bank performance. The variables are measured by different financial measures (bank performance is based on accounting, market value, and economic measures). Using structural equation modeling allows research variables to be measured correctly and multiple relationships between variables to be well tested, which has not been considered in previous studies. As new joint-stock companies were formed in Iran, owners gradually entrusted more responsibility to managers, resulting in the separation of ownership from management becoming

one of the essential issues of organizational theory on banks' financial health.

In the following sections, first, the theoretical foundations of the research topic and the relationship between variables are explained. Then the background of related studies is presented. In the following, hypotheses and research methods have been developed. The sample, measuring the variables, and data collection are explained. Data analysis and hypotheses testing using structural equation modeling and model goodness of fit are presented. Finally, conclusions and discussion of the research findings are discussed, respectively.

2. Literature Review

Effective corporate governance practices are based on objective assessments of management performance. The bank's board of directors was well-structured; there was a high degree of openness; and there were independent and competent internal committees that contributed to increased trustworthiness. Enterprises that used these governance structures had a reduced credit risk, according to Broadstock et al. [3]. The results of Scherer and Scherer et al. [4] research demonstrated that these governance measures enhanced financial performance within organizations. When crises struck, specific boards could convey positive signals to depositors and other key stakeholders by building confidence [5]. Khatib and Ibrahim Nour [6] suggest that an expanded board of directors might ensure more diversified expertise, better monitoring systems, and better communication during crises.

Other studies, on the other hand, found little evidence of a substantial and direct effect of corporate governance structure and qualities on the banking industry's performance throughout the pandemic era. Demir and Danisman [7] researched 1927 banks from 110 countries during the first four months of 2020. They discovered that governance scores had no meaningful effect on bank returns during the COVID-19 outbreak. These findings corroborate those of Takahashi and Yamada [8]. They examined the effect of several variables on Japanese stock returns during the COVID-19 epidemic. Similarly, the research showed that board independence was not a significant predictor of bank performance during the epidemic [9].

Corporate governance can be considered legal, cultural, and institutional arrangements that determine the direction of companies' movement and activity. This governance's components and mechanisms include shareholders and their ownership structure; board members and composition; the company's management, which is led by the CEO; and other stakeholders that can influence the company's movement. Among these, what attracts the most attention is the increasing presence of institutional and legal investors in the circle of public company owners and the effect that this group's active presence has had on how companies are run and, consequently, their performance [10].

The influence of intellectual capital efficiency and corporate governance systems on the annual report readability of Oman's financial sector enterprises was investigated by Dalwai et al. [11]. Design/methodology/approach: the outcomes of this study showed that higher readability of annual reports for financial sector organizations was connected with a drop in intellectual capital efficiency. On the other hand, banks indicate a favorable relationship between intellectual capital efficiency and the annual report's Flesch Reading Ease Score. Annual report readability is also adversely correlated with structural capital and capital used efficiency. Dispersed ownership and the size of the audit committee are examples of corporate governance processes that produce easy-to-read annual reports, which support agency theory.

Pourmansouri et al. [12] looked at the relationship between significant shareholders' power and the CG modality of firms. The findings of this study demonstrated that the concentration of ownership harms CGS quality, and significant shareholders cannot oppose the authority of the main shareholder; it also has a negative impact on the quality of corporate boards. Before and after the COVID-19 pandemic, the competitiveness and voting rights of significant shareholders had a negative impact on the quality of board membership. The most significant obstacles experienced in building, deploying, and managing such systems in Iranian SOEs were outlined by Beygi et al. [13]. Themes/challenges were derived from the data gathered using semistructured interviews and thematic analysis methods in an exploratory way and then examined and explained. The problems identified in the data set were then divided into four categories: "general assembly shortcomings," "ownership context concerns," "board deficiencies," and "external managerial restraints."

The influence of nonfinancial sustainability reporting (NFSR) on corporate reputation and the role of the CEO in the opportunistic behavior of businesses listed on the Tehran Stock Exchange were investigated by Zimon et al. [14]. The findings demonstrated that the CEO's power had little impact on the GSR-corporate reputation connection. Because businesses listed on the Tehran Stock Exchange are closely monitored, such as in governance, the influence of a CEO's power and the relationship of a CEO's power and GSR on corporate reputation examined in this study may not apply to these firms.

During the period 2011–2017, Salehi et al. [15] examined the association between certain corporate characteristics and management entrenchment in businesses listed on the Tehran Stock Exchange. Four corporate characteristics, namely real earnings management, predictable earnings management, institutional ownership, and board independence, were found to have a substantial link with managerial entrenchment, according to the findings. Using data from three areas, Hussain et al. [16] identified the influence of a country's governance limitations on Islamic and conventional bank income efficiency. To determine the amount of bank revenue efficiency, nonparametric data envelopment analysis was used. The study discovered that the dimensions of voice and accountability had a favorable impact on Islamic and conventional bank revenue efficiency but that political stability, the lack of violence, and corruption control had a negative impact. In addition, other aspects of regulatory quality, government efficacy, and rule of law are

all negatively correlated with traditional bank revenue efficiency.

The influence of openness and disclosure on banking financial results was investigated by Oino [17]. The focus was on evaluating openness and disclosure, auditing and compliance, and risk management as indicators of corporate governance, as well as understanding how these factors impact bank profitability, liquidity, and loan portfolio quality. In terms of statistical significance, the findings show that as the level of managerial reporting and transparency rises, capital market performance–as measured by loan portfolio quality, liquidity, and profitability–rises by 0.3046, with the effect statistically significant at a 1% level. Kamarudin et al. [18] looked at the impact of the global financial crisis on banks and the macroeconomic factors that influence profit efficiency in Bangladesh's banking industry. According to the findings, the determinants of capitalization, credit risk, and inflation have a considerable positive and negative impact on bank profit efficiency during the post-global financial crisis period. Aghimein et al. [19] looked at the technical efficiency, pure technical efficiency, and scale efficiency of Gulf Cooperation Council banks. The findings reveal inefficient resource management on the part of the managers. Furthermore, although larger banks tend to operate at constant or declining returns to scale, smaller banks are prone to operating at either returns to scale or growing returns to scale, according to the findings.

Kamarudin et al. [18] offered empirical data on the Bangladesh banking sector's profit efficiency and returns to scale. The empirical data appear to show that most Bangladesh banks have benefited from economies of scale as a result of being smaller than the ideal size or have suffered from diseconomies of scale as a result of being larger than the optimum size. As a result, cost savings or efficiency may be realized by reducing or raising the volume of manufacturing.

According to Akhigbe et al. [20], more openness lowers a company's cost of capital. They used the amount of analysts monitoring a holding company and the standard deviation of analysts' EPS projections to quantify transparency and the relationship between business transparency and bank holding company profit efficiency. Transparency has a beneficial influence on profit efficiency, according to the empirical findings. According to Kamarudin et al. [21], only in Islamic banks, revenue efficiency appears to be the critical factor contributing to lower or greater profit efficiency levels. This research also found statistically high cost, revenue, and profit efficiency differences between Islamic and conventional banks in GCC nations.

Corporate governance can play an essential role in improving corporate performance. There is a close relationship between the quality of corporate governance and corporate financial performance in capital markets. The process of monitoring and controlling the distribution of rights and responsibilities among shareholders, managers, and other participants and their decisions to serve shareholders' interests and improve company performance is made through the corporate governance mechanism. Therefore, one of the most critical factors affecting companies' financial performance can be considered corporate governance quality [22]. The two primary goals of corporate governance are: reducing firm risk through the improvement of accountability of managers and transparency as well as improving the long-term efficiency of the firm by preventing unwise decisions and authoritarianism and irresponsibility of the firm's executive management, both of which can lead to increase financial performance.

On the other hand, the company's ownership structure is another crucial factor that can affect the company's quality of company management, decisions, and performance. The ownership structure includes the texture or composition of ownership on the one hand and the degree of concentration of shares in shareholders' hands. However, studies have shown that different ownership structure dimensions and different owners groups do not have the same type and size in influencing the company's performance and decisions. Among the various groups of shareholders, institutional shareholders' ownership is one of the essential factors that can influence companies' decisions and management and, consequently, their financial performance. So, with the increase of institutional ownership due to the process of more supervision and control over the activities of executives, we can see an improvement in financial performance.

Managerial ownership is also an essential dimension of the company's ownership structure, affecting its shareholders' interests. Due to the lack of access to sufficient information, this factor has received less attention in research conducted on the bank's corporate governance. Managers whose wealth is mainly tied to investing in a bank are more likely to pay more attention to their bank and choose the risks they take more carefully than managers who have invested their wealth in various ways. More ownership of managers and board members alone should lead to more effort by these individuals, better bank performance, and less willingness to accept risk. In the case of board members, share ownership should incentivize managers to oversee and align their activities with shareholders' interests. The greater the concentration of wealth of a significant shareholder or board member in a bank, the greater the commitment to the bank and the greater the risk acceptance [23]. So, since a company's ownership structure can develop and improve corporate governance mechanisms or the system of governance face limitations, it can be expected that a good structure and appropriate governance system facilitate effective management and control of business units and subsequently improve internal processes and better company performance. This provides the basis for improving financial performance and achieving the long-term goals of shareholders and wealth creation for them.

Khoshtinat et al. [24], in their study, examined the effect of ownership structure on the performance of banks, using data from 13 banks. They examined performance with the variables of return on assets, return on equity, and ownership structure with dimensions such as private ownership, public ownership, ownership concentration, and credit risk. The results showed that the ownership structure has an insignificant effect on the functional dimensions of banks. At the same time, the concentration of ownership and credit

risk on performance variables has a significant inverse effect on corporate governance and significantly affects banks' performance. Ozili and Udiale [25] studied the relationship between ownership concentration and banks' profitability in developing countries. Their study showed that banks with a high degree of concentration present higher returns on assets, net profit margins, and revenue-generating power. Banks with a lower degree of concentration, on the other hand, have higher equity returns.

Rezaei and Mohammadzadeh [26] examined the impact of corporate governance on companies' financial performance and financial crises. They have tested the effect of corporate governance dimensions, including disclosure and transparency, the composition of the board, shareholders' voting rights, and ownership structure on companies' performance dimensions, including the Tobin Q index, the total return on assets, and return on equity. Their results showed that corporate governance's quality significantly affects total return on assets, return on equity, and company value. In contrast, an insignificant effect on the financial crisis of companies has been observed.

Mirchandani and Gupta [1] examined the impact of corporate ownership structure and governance on selected banks' performance in the UAE. The study results showed a significant relationship between corporate governance and bank performance. However, the ownership structure has an insignificant impact on bank performance. Faraji Dizaji et al. [27] investigated the effect of rent and political development on the independence of the Central Bank in oil-exporting countries. The results also indicate a positive association between central bank independence and improving the quality of political institutions. Therefore, according to the results, the increase in the rent income reduces the central bank's independence. Also, increasing the quality of institutions increases the central bank's independence.

Separation of ownership from management has led to the concept of corporate governance, which includes various mechanisms to monitor the work of executives to ensure efficient decision-making, maximize the value of the company, and affect bank performance. Hence, the relationship between the characteristics of the relationship between corporate governance and corporate performance and corporate governance on bank performance guidelines has been discussed in the literature of many companies. There is agreement on the relationship between corporate governance practices and company performance. However, this relationship is not very simple and direct. Especially during the global financial crisis, many companies went bankrupt despite effective corporate governance. The importance of this issue has been studied in many studies. One of the significant issues and challenges for companies surveyed in Iran has been addressed in this study. This study examines the effect of ownership structure and corporate governance components on bank performance. Corporate governance mechanisms, the board of directors, and supervisory mechanisms are determined by a company's structure, which includes the composition and concentration of ownership. Banks' activities are implemented and monitored through the corporate governance system. Therefore, the quality of banks' activities and performance will be primarily determined by their ownership structure and the quality of their governance. In the first part of the study, we simultaneously examine the effect of corporate governance and ownership structure on performance. A market-based measure (EVA) has been used to measure performance in addition to traditional accounting indicators, which provides an optimal measure of financial performance. Furthermore, the research approach and methodology are structural equation modeling, which has not been used in previous studies. It can therefore be a new approach in this regard.

3. Research Hypotheses

Based on the theoretical foundations and background conducted in this research, the following hypotheses have been developed and tested:

> H_1: The ownership structure significantly affects banks' corporate governance

Today, the performance of banks in equipping and allocating resources optimally can boost production, create jobs, and increase economic growth. An efficient banking system with the right monetary policy by controlling liquidity and inflation and directing resources to productive economic activities plays an essential role in economic development. However, the performance of banks is influenced by various political, economic, managerial, and social factors, and the study of these factors has been one of the topics of interest to researchers. In this study, the hypothesis of examining the dimensions of corporate ownership structure and governance over the performance of banks has been studied.

> H_2: The ownership structure has a significant effect on banks' performance

The most crucial feature of joint-stock companies is the separation of ownership from their management. Over the past 30 years, many cases of conflict of interest between groups and how companies deal with such conflicts have been raised by economists. These are generally referred to as "representation theory" in management accounting. The ownership structure is one of the essential issues of corporate governance that can affect the efficiency of companies by influencing managerial motivations. This study aims to investigate the asymmetric effect of ownership structure on banks' risk-taking behavior.

> H_3: Corporate governance studied that the relationship between ownership has a significant effect on banks' performance

Given that the issue of corporate governance has attracted a great deal of attention from economic actors in recent decades, in many countries, the ranking of companies in terms of corporate governance has begun, and after the financial crises of several Asian countries, laws to improve governance A company has been established. The question in this research is whether corporate governance practices

are improving in Iran and, in particular, whether it is possible to maintain and improve the financial health of Iranian commercial banks by using corporate governance procedures. Considering the major and significant effects of privatization, especially in connection with the privatization of banks and the conversion of credit financial institutions into banks, and the fact that many private banks operate in the primary and secondary capital markets, the effect of corporate governance on the financial health of commercial banks Iranian can be studied.

H_4: Corporate governance is mediating the relationship between ownership structure and bank performance

In other words, ownership of a government entity such as a bank has several drivers for overseeing financial reporting and improving corporate performance. Government-centered corporate governance system can potentially influence government industrial policies.

4. Research Design and Data Collection

According to its purpose, the present study is considered applied research since investors can use its results, managers, shareholders, capital market analysts, and listed banks on the stock exchange. In terms of the research methodology, it is a descriptive correlational study. Additionally, it is a documentary in terms of data collection. In addition to the 20 banks studied, included in the study are Mellat, Tejarat, Saderat, Pasargad, Parsian, Eghtesadnovin, Sina, Karafarin, Sarmayeh, Dey, Ansar, Gardeshgary, Hekmat Iranian, Iran Zamin, Saman, and Tose'e listed on Tehran Stock Exchange. The census examines Ayandeh, Postbank, and Ayandeh. We collected the data required to measure the variables from the Stock Exchange Organization database, the mentioned banks, and Iran's central bank from 2011 to 2017. We collected the data for the research variables from the audited annual financial statements of listed banks and the Tehran Stock Exchange and Rahavard Novin financial software information databases.

4.1. Research Variables. According to the research objective and to test the hypotheses, the variables are measured as follows.

4.1.1. Financial Performance. The dependent variable in this study is the financial performance of banks, which has been measured using three measurable components, including Tobin's Q ratio, return on equity ratio (ROE), and economic value added (EVA).

Tobin's Q ratio is calculated as the total book value of liabilities plus the equity market value divided by the book value of total assets.

Return on equity is measured by the net profit ratio divided by total equity.

Economic value added (EVA) is calculated as follows:

$$\mathrm{EVA} = \mathrm{NOPAT}_t - \left(\mathrm{WACC}_t \times \mathrm{Capital}_t\right), \tag{1}$$

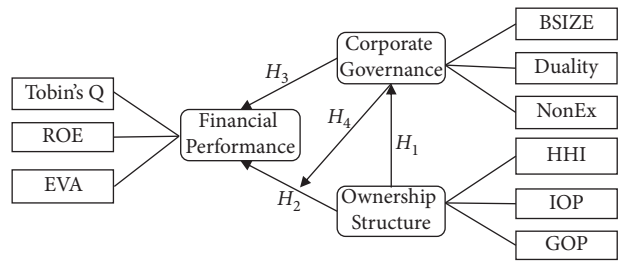

Figure 1: Conceptual framework and relationship between the research variables.

where NOPAT_t is the net operating profit after tax for year t, in the calculation of which the effect of noncash transactions are eliminated and tax savings resulting from financing costs are deducted from the profit and is calculated by the following equation:

$$\begin{aligned}\text{Operating profit after tax} = {} & \text{income adjustments}\\ & + \text{cost adjustments}\\ & + \text{interest tax shield}\\ & - \text{interest expense}\\ & + \text{after} - \text{tax profit},\end{aligned} \tag{2}$$

WACC_t is the weighted average cost of capital for year t, and $\mathrm{Capital}_t$ is the total capital employed in the business for year t.

4.1.2. Ownership Structure. To measure that as an independent variable, three components, including the Herfindahl–Hirschman index, institutional ownership ratio, and government ownership ratio, were used as follows:

Herfindahl–Hirschman index (HHI) measures the degree of concentration of ownership in the company. So that the closer the calculated index is to number one, the greater the concentration of ownership, and the closer this index is to zero, the greater the dispersion of ownership, calculated as follows:

$$\mathrm{HHI} = \sum_{i=1}^{k} s_i^2, \tag{3}$$

where S_i is the proportion of ownership of each shareholder in the company i.

Institutional ownership ratio (IOP) is measured by the ratio of shares owned by financial institutions such as banks, insurance companies, and pension funds to the company's total stock under review.

Government ownership ratio (GOP) is measured by the ratio of shares owned by government-affiliated organizations and companies to the company's total shares under review.

4.1.3. Corporate Governance. In this study, corporate governance plays the role of a mediator variable, which is measured by the three components of board size, the

proportion of nonexecutive members, and the duality role of the CEO as follows:

The number of board members measures board size (BSIZE).

NonEx ratio is measured by the number of nonexecutive members ratio to the total number of board members.

The CEO's duality role is considered a dummy variable that takes one if the CEO holds the chairman of the board and zero otherwise.

Figure 1 presents a conceptual framework to illustrate the relationships between the variables for testing the research hypotheses.

4.2. Data Analysis. The structural equation modeling method has been used to analyze the data and test the research hypotheses. The first generation of structural equation methods is covariance-based methods. The primary purpose is to validate the model and require high-volume samples to work. The second generation of structural equation methods is variance-based models. Later renamed the partial least squares (PLS) method, these methods provided different data analysis methods than the first generation. The most important software for this method is smart PLS. Researchers have cited several reasons for using the method, and the most important reason is the superiority of small samples. The following reason is the existence of abnormal data that researchers face in some studies [28].

In this research, the goodness of fit for each latent variable is investigated after standardizing the calculated values for the components of each observed variable based on the values of their factor loads and significance. Then the hypotheses are tested based on path coefficients, and the latent variables and their significance are discussed.

5. Results and Discussion

The following section presents descriptive statistics of the research variables for 126 observations. Table 1 shows the summary of descriptive statistics of the variables. As seen, the mean of Tobin Q equals 2.234 with a standard deviation of 1.551. Return on equity equals 0.062 with a standard deviation of 0.091, and economic value added equals 279,028 Rls with a standard deviation of 102,126 Rls. On the other hand, the mean of Herfindahl–Hirschman is equal to 0.592 with a standard deviation of 0.283. The ratio of institutional ownership is 0.746 with a standard deviation of 0.229, and the ratio of government ownership is 0.096 with a standard deviation of 0.0208. Also, the mean board size equals 6.402 with a standard deviation of 2.127, and the ratio of nonexecutive board members equals 0.518 with a standard deviation of 0.314. The table does not include descriptive statistics of the CEO's variable dual role as a dummy variable with zero values and one.

As mentioned in the previous section, three components have been used to measure each research variable. Therefore, it is necessary to use structural equation modeling to test the goodness of measuring each latent variable using observed variables. Then these variables are used to test the hypotheses. The measurement of latent variables is presented as follows.

Table 1: Descriptive statistics of research variables.

Variable	No.	Mean	Std. Dev.	Min	Max
Tobin's Q	126	2.234	1.551	1.012	4.029
ROE	126	0.062	0.091	−0.127	0.345
HHI	126	0.592	0.283	0	0.96
IOP	126	0.746	0.229	0.069	0.994
GOP	126	0.0396	0.0208	0	0.10
BSIZE	126	6.402	2.127	4	11
NonEx	126	0.518	0.314	0.214	0.736

5.1. Ownership Structure. As mentioned previously, Herfindahl–Hirschman index (HHI), the ratio of institutional ownership (IOP), and the ratio of government ownership (GOP) were used to measure the ownership structure variable. Table 2 shows the goodness of fit for the variable. The table shows that the value of χ^2 normalized to the degree of freedom is less than 3, and its P value is less than 0.05. On the other hand, the goodness of fit index (GFI) value equals 94.558. In contrast, the adjusted value (AGFI) equals 92.312, more than 90%. Also, the root value of the mean squares of the estimation error (RMSE) is equal to 0.014 and less than 0.05. Therefore, according to the above values, it can be concluded that the measurement of the ownership structure's latent variable based on the model's apparent variables is significantly appropriate.

5.2. Corporate Governance. Three variables, including board size (BSIZE), the ratio of nonexecutive board members (NonEx), and the dual role of the CEO (duality), have also been used to measure the corporate governance of the banks. Table 3 shows indices of the goodness of fit for the variable. The table shows that the value of χ^2 normalized to the degree of freedom is less than 3 with a significance level of less than 0.05. On the other hand, the goodness of fit index (GFI) value is equal to 94.368; its adjusted value (AGFI) is 92.212; and both are more than 90%. The root value of the mean squares of the estimation error (RMSE) is equal to 0.015 and less than 0.05. Therefore, the obtained values indicate that the mentioned observed variables can be significantly used to measure corporate governance's latent variable.

5.3. Financial Performance. Three variables, including Tobin's Q ratio, ROE, and EVA, have already been used to measure the latent variable of financial performance. Table 4 illustrates the indices of the goodness of fit for the variable. As seen in the table, the value of χ^2 normalized to the degree of freedom is less than 3 with a significance level of 0.036 (less than 0.05). Also, the goodness of fit index (GFI) is equal to 94,062 with an adjusted value (AGFI) of 91.816 and more than 90%. On the other hand, the root value of the mean squares of the estimation error (RMSE) for the variable is equal to 0.016 and less than 0.05. Therefore, as in the previous variables, it can be said that the goodness of fit of the

Table 2: Goodness of fit indices of ownership structure.

χ^2/df	P-value	RMSE	GFI	AGFI
2.92	0.030	0.014	94.558	92.312

Table 3: Goodness of fit indices of corporate governance.

χ^2/df	P-value	RMSE	GFI	AGFI
2.73	0.032	0.015	94.368	92.122

Table 4: Goodness of fit indices of financial performance.

χ^2/df	P value	RMSE	GFI	AGFI
2.43	0.036	0.016	94.062	91.816

latent variable of financial performance based on the apparent variables is significantly appropriate.

5.4. Model Estimation. After analyzing the goodness of fit to measure research variables, a structural model was obtained, indicating the relationship between latent variables of research. Figure 2 shows the general model of the relationship between research variables using the partial least squares (PLS) method.

Finally, based on the structural equation modeling according to the figure, Table 5 shows the factor loading of the observed variables with significance levels. Based on the value of the t-statistic and significance level related to observed variables, the table's findings show that all observed variables significantly affect (at least 90%) latent variables.

In the following, CR and AVE indices have been used to evaluate the convergent reliability and validity of the structures, using equations (4) and (5):

$$\mathrm{CR} = \frac{\left(\sum \lambda\right)^2}{\left(\sum \lambda\right)^2 + \left(\sum \delta\right)}, \tag{4}$$

$$\mathrm{AVE} = \frac{\sum \lambda^2}{n}, \tag{5}$$

where λ represents the standardized factor load of the indices and δ represents the standard error symbol. CR coefficient greater than or equal to 0.7 indicates good reliability. A value of at least 0.8 means very good reliability. If the value is greater than or equal to 0.9 shows excellent reliability of the indicators. If the AVE index for each variable is more than 0.5, the construct in terms of convergent validity is appropriate [28]. Table 6 shows the results of these indicators for latent variables. As it is seen, the CR coefficients for all variables indicate the good reliability of the structure. Since the AVE coefficients are higher than 0.5, the constructs' convergent validity can be observed as well.

Divergent validity, which indicates a latent variable with its indices compared to the relationship between that variable and other variables, is examined as follows. Appropriate divergent validity of a model indicates that one variable in the model interacts more with its indices than with other variables. Therefore, each variable's AVE coefficient must be greater than the correlation between the variable and others [29]. Table 7 shows the Fornell–Larker matrices and the divergent validity of the variables. The primary diameter of the variables' correlation matrix shows the variables' square root. As can be seen, the AVE index's square root for both variables is more significant than their correlation values, so it can be concluded that divergent validity is appropriate for all three variables.

After examining the goodness of fit of the variables and measuring the reliability and validity, Table 8 represents the structural model's result of testing the hypotheses. As can be seen, the direct effect of research variables on each other and the indirect effect of ownership structure on financial performance due to corporate governance have been estimated using path coefficients. Their significance level has been shown as well.

The findings of Table 8 show that the direct effect of ownership structure (OS) on corporate governance (CG) with a path coefficient of 0.44 with a significance level of 0.114 is insignificant, while the effect of ownership structure (OS) on financial performance (FP) with a coefficient of −0.68 and a significant level equal to 0.015 is significant. The direct effect of corporate governance (CG) on financial performance (FP) with a coefficient of 0.78 and the significance equal to 0.005 also shows the significance of the estimated coefficient. The findings of the table also show that the indirect effect of ownership structure (OS) on financial performance (FP) through corporate governance (CG) as an intermediate variable with a coefficient of −0.57 and a significant level of 0.041 shows that the indirect effect is significant as well. In other words, corporate governance reduces the severity of the ownership structure's negative impact on bank performance. Based on the above findings, it can be concluded that the first hypothesis of the research failed to confirm. In contrast, the second, third, and fourth research hypotheses and corporate governance's mediating role have already been confirmed. The results are consistent with parts of the findings of Nakhaee and Zahraei [2], Akimova and Schwodiauer [30], Spong and Sullivan [31], Wanjiru et al. [32], Ozili and Uadiale [25], and Mirchandani and Gupta [1] while tending to be inconsistent with some of the findings of, Rahimian et al. [33], and Shahikitash et al. [34].

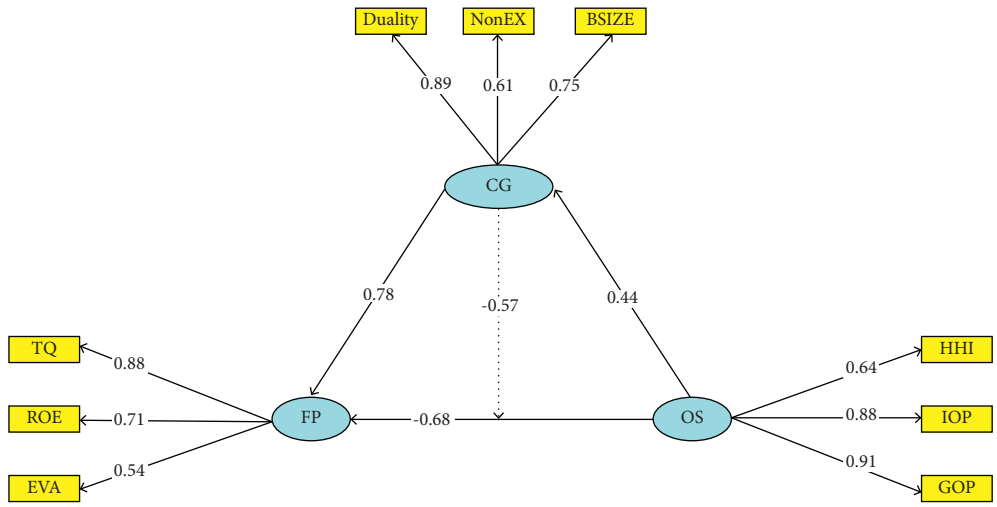

Figure 2: Measurement and structural model.

Table 5: Significance of the measurement model.

Latent variables	Observed variables	Factor loading	t value	P value
Ownership structure (OS)	HHI	$\lambda_1 = 0.64$	2.291	0.022
	IOP	$\lambda_2 = 0.88$	3.151	< 0.001
	GOP	$\lambda_3 = 0.91$	3.258	< 0.001
Corporate governance (CG)	BSIZE	$\lambda_4 = 0.75$	2.685	0.004
	NonEx	$\lambda_5 = 0.61$	2.184	0.030
	Duality	$\lambda_6 = 0.89$	3.186	< 0.001
Financial performance (FP)	Tobin's Q	$\lambda_7 = 0.88$	3.151	< 0.001
	ROE	$\lambda_8 = 0.71$	2.542	0.011
	EVA	$\lambda_9 = 0.54$	1.933	0.054

Table 6: Results of reliability and validity of the constructs.

Latent variables	Coefficient CR	Coefficient AVE
OS	0.762	0.611
CG	0.791	0.638
FP	0.906	0.708

Table 7: Fornell–Larker matrices for divergent validity.

Variables	OS	CG	FP
OS	0.782		
CG	0.517	0.799	
FP	0.623	0.638	0.841

Table 8: The effect of latent variables on each other.

Effect	Latent variables	Path Co.	T value	P value
Direct effect	OS ----⟶ CG	$\gamma_1 = 0.44$	1.575	0.114
	OS ----⟶ FP	$\gamma_2 = -0.68$	2.435^{**}	0.015
	CG ----⟶ FP	$\gamma_3 = 0.78$	2.793^{***}	0.005
Indirect effect	OS ---⟶ CG ---⟶ FP	$\beta_1 = -0.57$	-2.041^{**}	0.041

According to the obtained results, some recommendations can be made as follows:

(1) Capital market policymakers and institutional shareholders should be aware that the presence of nonexecutive members of the board of directors cannot reduce agency problems to help the company perform better, so try to make more use of executive members' presence.

(2) Given the importance of institutional investors and significant shareholders in the management of companies, mainly banks, it is suggested that these shareholders have a more active role in monitoring and controlling the activities of companies and align the interests of shareholders and managers to reduce agency problems. Furthermore, ultimately help improve company performance.

(3) It is also suggested that the board of directors, shareholders and auditors, and auditing firms are getting more informed about corporate governance issues, resulting in playing a proper role in corporate governance and thus increasing the company's value.

(4) Future researchers are encouraged to consider other performance indices such as the MVA index and the BSC and EFQM methods for conducting similar research.

6. Conclusion

Estimating the structural equation model indicates that all observed variables significantly affect latent variables. In other words, latent variables can be measured adequately based on observed variables. The results show that the direct effect of ownership structure on corporate governance is insignificant, meaning that the mechanism of corporate governance is not affected directly by ownership structure. Therefore, the first hypothesis of the study failed to confirm. Also, the ownership structure has a significant negative effect on financial performance. It means that by increasing the concentration of ownership at the disposal of a limited number of shareholders and the ratio of institutional to state ownership, the financial performance of banks decreases significantly and vice versa. Therefore, the second hypothesis of the research is significantly confirmed.

On the other hand, the effect of corporate governance on financial performance is also significantly positive, which shows that improving the corporate governance mechanism can significantly improve bank performance, so the third hypothesis of the study is confirmed as well. The results also show that the indirect effect of ownership structure through corporate governance on bank performance is significant. The fourth hypothesis is also confirmed. It means that good corporate governance reduces the severity of the ownership structure's negative impact on the bank performance under review.

The results show that the shareholding of government-affiliated institutions and companies and financial institutions, especially when they have a majority stake, causes these shareholders to pursue their own goals and interests instead of considering the total interests of shareholders and the value of banks, leading to poor financial performance. This issue supports the hypothesis of convergence of interests, according to which large institutional shareholders have a strategic alliance with the company's management. As a result, instead of pursuing all shareholders' interests, managers will be given to large institutional shareholders and work in their best interests. Also, according to the strategic alignment hypothesis, institutional shareholders' expectations sometimes may be tied to managers' interests. Due to the matching of the interests of the two groups, microshareholders' interests are ignored, reducing the expected beneficial effects.

On the other hand, appropriate corporate governance mechanisms can increase the financial performance of banks because one of the possible reasons for the above conclusion is the participation of executive and nonexecutive directors of the board in the activities and their supervisory role in banking operations. There is also evidence that the board's large size can help CEOs through consulting play an influential role in corporate performance.

Data Availability

The data used to support this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

News Sentiment and the Risk of a Stock Price Crash Risk: Based on Financial Dictionary Combined BERT-DCA

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This study combines a financial knowledge dictionary and pretraining method based on BERT (Bidirectional Encoder Representation from Transformers) to construct a deep learning model for identifying stock news sentiments. The study then calculates the sentiment metrics of all stocks and analyzes the impact of news sentiment on the risk of a stock price crash and its heterogeneity. The results show that stocks with more positive sentiment metrics have a higher risk of crash in the following year. We also investigate the information intermediation and investor sentiment channels by which news sentiment affects the risk of a crash. The results show that more net insider sales, lower information transparency, and less analyst coverage amplify the impact of news sentiment on future crash risk, which is consistent with the information intermediation channel. Additionally, more retail investor positions, more active investor sentiment, and divergence between analysts' opinions and news amplify the impact of news sentiment on the risk of a future stock price crash, which is consistent with the investor sentiment channel.

1. Introduction

Stability is a necessary condition for the financial market to efficiently facilitate economic development. In developing countries with weak financial infrastructure and low market efficiency, the risk of firm-specific stock price crash can seriously threaten investors and undermine their confidence in the stock market. The regularly used method of portfolio diversification cannot fully mitigate it, leading researchers to focus on the factors inducing stock price crash. A different strand of literature investigates the effects of media coverage or overall media tone on stock price crash risk, to which the present study belonged. We, however, adopted a slightly different perspective—the asymmetric impact of sentiment heterogeneity (i.e., positive or negative).

Our study aims to examine the asymmetric impact of news sentiment on stock price crash risk attributable to the role of media as information intermediary that influences investors' sentiment. On the one hand, regardless of the bias of media coverage, positive news will inevitably lead to investors' optimism. The media report positive news about some firms, according to the theory of the spiral of silence [1], pessimistic investors may remain silent and optimistic investors may dominate the market. When short selling is not allowed, pessimism about that firm cannot be hedged normally. Subsequently, a stock price crash will happen when the optimistic sentiment dissipates and pessimistic investors become the marginal buyers [2]. On the other hand, the management has every intention of defending the firm's image and concealing negative information from the public [3, 4], which unintendedly leads to an overvaluation of stock prices, resulting in price bubbles. When the management can no longer delay or conceal negative news and has to release it to the market in a short period, the pessimism of investors will be amplified, inducing a stock price crash [5–8].

We distinguish among the sentiments of the media coverage and study the asymmetric impacts of positive and negative news on stock price crash risk. Thus, we need a precise measurement of the sentiment for objectively evaluating the tone and extent of the news. In this regard, a burgeoning body of finance and accounting literature has used natural language processing (NLP) algorithms to

extract the financial texts' sentiment [9–12]. The emergence of modern deep learning algorithms, such as ELMo, GPT (generative pretraining), and Google BERT, makes NLP move up a gear in the accuracy of sentiment analysis. Related studies have suggested that relative to traditional methods, modern deep learning algorithms that combine prior knowledge in certain fields have better performance. In this study, we customize a state-of-the-art deep learning NLP algorithm (BERT) for financial texts and document its advantages over traditional approaches.

We collect a total of 1,132,856 initial media coverage articles between 2011 and 2020 from the China Stock Market and Accounting Research database [13]. We manually construct our own sentiment dictionary in the financial domain and use it as a corpus for sentiment classification. Moreover, the BERT-based pretraining model is designed to help machines understand the characteristics of human language and extract sentiment information effectively. Based on the model, we classify the related news of each stock. Finally, our sample consisted of 17,267 firm-year observations representing 2,277 individual firms.

To begin with, we examine whether media sentiment is associated with a firm-specific future price crash risk. We measure media sentiment from three dimensions: mixed (on average), positive, and negative sentiments. We define the indicators of the average sentiment and those of the positive and negative sentiment, respectively. We use three proxies of stock price crash risk: the binary variable (CRASH) that equals 1 for a firm-year that experiences one or more crash weeks during the fiscal year and 0 otherwise; the negative coefficient of skewness of firm-specific weekly returns (NCSKEW); and the down-to-up volatility (DUVOL) of firm-specific weekly returns [3, 14, 16]. The results show that firms with more positive media coverage tend to have a higher risk of future stock price crash. Meanwhile, negative media coverage shows a limited effect on the risk of future stock price crash and a significant negative relation with current stock price crash risk, implying that they can lead to a stock price crash in the short term.

We then address the natural question of identifying the channels through which media sentiment affects the stock price crash risk. We hypothesize two possible channels, namely, information intermediation and investor sentiment, and then design various settings to examine them. The stock market is significantly impacted by the media, as an important information intermediary between firm management and market participants. On the one hand, media outfits disseminate value-relevant information on firms' current and future earnings to outside investors, reduce market frictions, improve investor perceptions, and mitigate information asymmetry [14, 17, 18]. On the other hand, media are not the perfect messengers. Media coverage is not always objective and neutral, but rather offers ambiguous, out-of-date, and even exaggerated and biased contents [19, 20]. According to previous findings, more net insider sales, lower information transparency, and less analyst coverage amplify the impact of media sentiment on future crash risk, which is consistent with the "information intermediation" channel.

Investors, owing to their limited attention and overconfidence, can be expected to overreact to catchy, anecdotal, and less relevant information, but underreact to abstract, statistically listed, and relevant information [21]. Furthermore, they may exhibit confirmation bias, which is the tendency to seek and believe information that supports one's beliefs while ignoring later signals that are inconsistent with their prior beliefs after developing a favorable impression of a firm [22]. As such, media coverage of firms (particularly positive news), regardless of whether the content is outdated or not, can easily pique the interest of investors, causing them to overreact or overestimate a firm's prospects and bring about a short- or long-term increase above the fundamental value [23–25]. However, when actual operational problems are revealed or a firm fails to meet expectations, negative sentiment will emerge and the stock price will reverse, resulting in a crash; this process will be reinforced when media coverage is biased and exaggerated. More retail investor positions, more active investor sentiment, and divergence between analysts' opinions and media coverage amplify the impact of news sentiment on future crash risks, which is consistent with the "investor sentiment" channel.

We expect to contribute to the literature in the following ways. First, our work also adds to the growing literature on the determinants of firm-specific price crash risk. Numerous studies have established a link between media sentiment and stock prices [7, 22, 26–28]. Sentiment in news articles contain novel information on stock prices [7, 8], but few studies have paid attention to the relation between the media sentiment's asymmetric effect on the future firm stock price crash risk. We attempt to fill this gap. We provide the formal piece of empirical evidence that positive news sentiment predicts a higher firm-specific future price crash risk, whereas negative sentiment increases the current crash risk. We provide a thorough examination of the impact of media sentiment from both perspectives of inspiration of investor sentiment of media tone and information economics, revealing new evidence that investors' irrational and excessive optimism could be a major cause of stock price bubbles and crashes in China, where retail investors predominate and short selling is restricted.

Second, our research study combines advanced deep learning and dictionary methods, which take full advantage of the performance and intelligence of computer technology and greatly improve the identification accuracy and efficiency of massive sentiment information. The sentiment dictionary approach uses word and syntactic analyses of text to calculate sentiment values as the basis for determining text sentiment tendencies. However, individuals can add necessary semantic words, such as praise words, degree adverbs, and negative words, which play an important role in enhancing or weakening sentiment semantic words [21]. Sentiment dictionary classification methods, which ignore the characteristics of language, such as grammar, context, and subjective construction methods, are likely to have the problem of omission. We attempt to mitigate this problem through integrating a cutting-edge deep learning method. To the best of our knowledge, this study is the first to combine

deep learning and dictionary methods to perform sentiment analysis in the financial field, thereby extending the application of sentiment analysis methods in the financial field.

Third, our study contributes to the literature on text analysis in the economic field [4, 29]. We introduce BERT, a deep learning pretraining model, and combine it with a relatively mature sentiment dictionary. Using the BERT pretraining model, researchers can take full advantage of the contextual information in the news. The vector expression of the same words is different between news and contexts, which was difficult to address in previous studies. In the pretraining model, by pretraining large text corpora as a language model, we create embeddings for the context associations (embedding) of each word in a sentence, which could then be entered into subsequent tasks, thereby enabling a full quantification of the information contained in the text.

2. Theory and Hypothesis

The media, as an important vehicle for information dissemination, play a significant role in the risk of stock price crashes. SentimentsGiven the content of a media news, the sentiment contained in the content matters. Pure positive or negative news, which may mask the firms' actual situation, can exacerbate information asymmetry between firms and outside investors. In addition, the problems of irrational sentiment, herding effects, and "chasing the upside and killing the downside" phenomenon are aggravated by biased news. Both channels can increase the risk of a stock price crash. Considering the preceding ideas, we formulate the following competing hypotheses:

Hypothesis *H1a*: Higher average media sentiment can exacerbate the future stock price crash risk.

Hypothesis *H1b*: Higher average media sentiment can alleviate the future stock price crash risk.

We also examine the heterogeneous effect of sentiment in news on future stock price crash risks. When the media exaggerate the positive parts of news, they send positive signals on the firms to outside investors. With information asymmetry, investors will overestimate the firms' value, which can lead to abnormal stock price increases. As short selling is not allowed in China, rational and pessimistic investors are unable to engage in the market and stock prices will continue to increase until investors realize that there is an overvaluation component in the news. According to Solomon [28], the media's whitewashing behavior of overusing positive terms to disclose the information of listed firms can lead to a sharp decline in stock prices. Therefore, intense positive news can increase the stock price crash risk.

Alternatively, related research studies reveal the tendency of firm management to conceal negative information from the public [3, 30], which inevitably leads to an overestimate of the firm value, resulting in higher stock prices. Simultaneously, retail investors are more sensitive to negative news [31]. When the management has no choice but to release negative information to the market, retail investors will sell-off stock holdings, which increases the risk of a stock price crash [32]. Therefore, the coverage of negative news can increase the risk of stock price crash. Considering the preceding ideas, we hypothesize as follows:

Hypothesis *H2a*: News with positive sentiment can exacerbate the future stock price crash risk.

Hypothesis *H2b*: News with negative sentiment can exacerbate the future stock price crash risk.

Subsequently, we then proceed with identifying the underlying mechanisms. We hypothesize that the impact may come from the two channels of "information intermediation" and "investor sentiment."

According to Jin and Myers [33], when there is information asymmetry, the agency problem, such as management's rent-seeking and concealment of negative news, can affect the share price crash risk significantly. Insiders have information that is not yet publicly available, which can be used to assess the value of the company and predict future firm performance [34]. Insider sell-off behavior is positively associated with the risk of a stock price crash [35]. The insider's choice to sell stocks sends negative signals to outside investors, thereby raising the probability of a future crash risk. Based on the explanation above, we hypothesize the following.

Hypothesis *H3a*: The impact of media sentiment on the future stock price crash risk is enhanced when insiders have more net sales of stock.

Information asymmetry can prevent investors from knowing the firm's actual operation and investors may be deceived by false public information. Especially, firms whose information transparency is low and those whose management is more likely to hide bad news are more likely to experience a sharp stock price fall in future [3]. When financial opacity is high, investors cannot fully grasp the true state of a firm through public information. They will rely more on the media coverage to make investment decisions, which will amplify the role of media sentiment. Therefore, we hypothesized as follows.

Hypothesis *H3b*: The impact of media sentiment on the future stock price crash risk is enhanced when the firm has higher financial opacity.

Analysts serve as both information intermediaries and management monitors [36]. They acquire and process data about firms using public information, field research, and other sources and reduce information asymmetry between firms and investors [37, 38]. According to He et al. [35], analyst coverage reduces stock price crash risk via analysts' role as information intermediaries and monitors. Nonetheless, when analysts cannot fully perform the information intermediary role, it is more difficult for investors to learn the real situation of the firm and they cannot accurately identify the noise in the media coverage; thus, the impact of media sentiment on future stock price risk is more evident through driving the investors' decision-making process. We thus hypothesize as follows:

Hypothesis *H3c*: The impact of media sentiment on the future stock price crash risk is enhanced when the firm has lower analyst coverage.

Next, we test the existence of the "investor sentiment" channel.

The sentiment of media affects investors differently. Institutional investors have more information and a specialized ability; therefore, it is easier for them to judge the validity of the information contained in the news. Sentiments in news thus have a limited influence on institutional investors. Conversely, retail investors do not have the information and skills possessed by institutional investors; thus, sentiments in news have a greater impact on retail investors. Therefore, we formulate the following hypothesis:

Hypothesis *H4a*: The impact of media sentiment on the future stock price crash risk is enhanced when the stock has a higher proportion of retail investors.

Investors may place great faith in catchy, anecdotal, and low-relevance information and overreact to it as a result of limited attention and overconfidence [21]. They may also exhibit a confirmation bias, which is the tendency to seek and believe information that supports one's beliefs while ignoring later signals that are inconsistent with prior beliefs after developing a favorable impression of the firm [22]. Thus, positive media coverage of firms attracts investors' attention, thereby causing them to overreact or form overexpectations about the firm's prospects, resulting in a stock price that is briefly or chronically above the underlying value. Therefore, we proposed the following hypothesis:

Hypothesis *H4b*: The impact of media sentiment on the future stock price crash risk is enhanced when investors are more optimistic.

Heterogeneous beliefs among investors increase when analysts' opinions differ from the sentiment of media coverage. In the absence of a short selling mechanism, more optimistic investors are expected in the market in the short term. However, over time, pessimistic beliefs will eventually emerge, which will increase the likelihood of a future stock price crash. Therefore, we hypothesize as follows:

Hypothesis *H4c*: The future stock price crash risk increases when analysts' points disagree with the sentiment of media.

3. Sentiment Extraction Model Design

Our study obtains financial news data for the period January 2017 to December 2020 from the China Stock Market and Accounting Research database. We preprocess the data by deleting special symbols and irrelevant information. We select 3,305 news items from the 1,132,856 news texts to label the news regarding the financial entities as positive or negative sentiments and added them to the financial sentiment dictionary manually. Using the BERT pretraining model and financial sentiment dictionary-based attention mechanism, we classify the sentiment of 1,132,856 news items. We then derive the average sentiment index of each stock in each year using the weighted average of all related news sentiment.

3.1. Data Preprocessing. We construct a microsentiment corpus in the financial field. To avoid interference with the hard data contained in the news, we eliminate the company announcements and then preprocess the text by removing special symbols and using regular matching to remove irrelevant information.

3.1.1. Data Clean-Up. We label the financial entities: we identify the company, person, and brand names in the text. Entity names are marked based on the principle of long matching. We also identify the company and brand names with the help of "Tianyancha." For example, in the following text, "Runtu Shares: Ruan Jiachun (Chairman) plans to reduce no more than the total share capital of 1.28," "Runtu Shares" and "LeTV" are marked as entities.

3.1.2. Label News Sentiment. The sentiment polarity of financial entities is grouped into three categories—neutral, negative, and positive. Each category is defined as follows and Table 1 shows the distribution.

Positive sentiment: The text is marked as positive if the fact favors the operation of the company and there are some artificial positive comments. For example, "Southeast network frame won the bid of 357-million-yuan project."

Negative sentiments: If the information in the text is bad for the company's operation because it includes some facts that are bad for the operation of the company and artificial negative comments. For example, "Tianmaotui will be delisted from the Shenzhen Stock Exchange on July 20."

Neutral sentiment: Unlike positive and negative sentiments, the labeling of neutral sentiments is relatively complex. The text information is related to the operation of the company but cannot be judged as favorable or unfavorable, or it has both favorable and unfavorable facts. For example, "e-commerce is the direction of future development, all enterprises are making efforts. So does Huawei, but at present, the effectiveness needs to be tested."

To construct a microsentiment analysis dataset in the financial field, we select 4,516 samples from the 1,132,856 news texts obtained for annotation. After the independent annotation, all annotators discussed the additional annotations noted in the case of objectionable or uncertain results until consensus was reached. The annotation data were artificially modified and the annotation was completed.

Finally, 3,644 financial entities are sorted out. Each financial entity corresponds to one or more sentences. Each article has a total of 10,112 sentiment sentences. Based on prior financial knowledge, we construct a sentiment dictionary in the financial domain, which contains 2,842 positive words, 1,230 neutral words, and 2,043 negative words (Table 2).

3.2. BERT Pretraining Model. In 2018, Google proposed the natural language pretraining model, BERT, in the article "BERT: Pretraining of Deep Bidirectional Transformers for Language Understanding." Training of the BERT model mainly includes the following two steps.

Table 1: Financial entities.

	Positive	Neutral	Negative
Nums.	4,179	3,202	1,627
Pct	46.39%	35.55%	18.06%

The sentiment polarity of financial entities is grouped into three categories—neutral, negative, and positive.

Table 2: Financial dictionary.

	Positive	Neutral	Negative
Nums.	2,842	1,230	2,043
Pct	46.48%	20.11%	33.41%

The authors construct a sentiment dictionary in the financial domain, which contains 2,842 positive words, 1,230 neutral words, and 2,043 negative words.

BERT pretraining: The pretraining of BERT helps it learn the characteristics of a character, a word, statement levels, and understatement relationships among massive text data through simultaneous two pretraining tasks—masked language model and next sentence prediction. During pretraining, the same corpus is inputted into the model multiple times, but each input is preprocessed in different forms, allowing the same corpus to be fully utilized. For users, the pretrained models and parameters can be downloaded from the Internet and can be directly fine-tuned without having to do pretraining themselves, which reflects the convenience of BERT.

Fine-tuning: On the basis of the pretrained model, an output layer is customized and added to specific downstream tasks, such as text sentiment classification and sequence annotation. Then, the data from downstream tasks are used to fine-tune the model to generate models with higher prediction accuracy for various NLP tasks.

BERT uses a more powerful bidirectional transformer encoder (Figure 1) along with the masked language model and next sentence prediction (NSP) as an unsupervised goal, to enable the vector representation of each word and word output by the model to describe the overall information of the input text as comprehensively and accurately as possible. Thus, BERT provides better initial values of model parameters for subsequent fine-tuning tasks. Its input embedding is constructed by summing the token, segment, and position embedding of the corresponding word. It also contains more parameters, which gives it a stronger word vector embedding ability.

3.3. Construction of BERT-DCA Model. We construct a BERT-DCA model (Figure 2) that combines the financial sentiment dictionary and attention for sentiment analysis. Two information processing channels—left semantic information attention channel (SAC) and right sentiment information attention channel (EAC)—are adopted in the structure. The SAC extracted semantic information, whereas the EAC allowed the model to pay attention to the particularity of different types of words to supplement the weights and obtain more information as a supplement to word-level information.

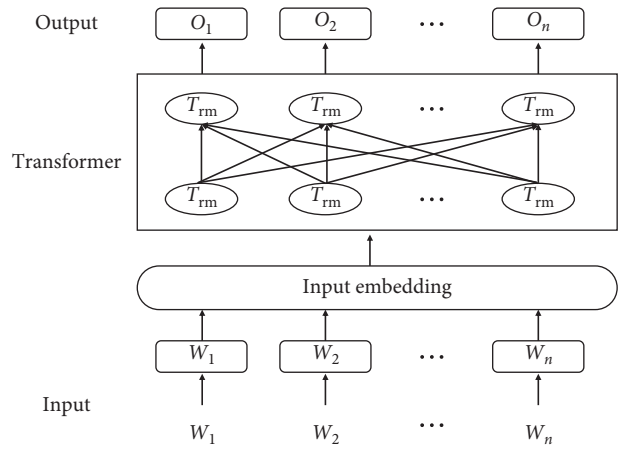

Figure 1: BERT model structure.

3.3.1. Input Layer. For the text sentence sequence, after word partitioning, the word sequence $\{W1, W2, \ldots, Wn\}$ is used as the input for SAC. Based on the domain sentiment dictionary and financial entities, words are classified into the following five categories: Pos, Neg, Neu, Entity, and Other, which denote positive, negative, neutral, financial entities, and others, respectively. They are from the sentimental dictionary discussed above. Then, we derive the sentimental information word collection $\{E1, E2, \cdots, Em\}$ as the input of EAC. We then use the pretraining model, BERT, to provide the word vector, which can achieve the dynamic adjustment of the word vector with the context, and train the real sentiment semantic embedding model to obtain the semantic information word vector matrix R_x and the sentiment information word vector matrix R_e.

$$R_x = x_1 \oplus x_2 \oplus \ldots \oplus x_n, \tag{1}$$

$$R_e = e_1 \oplus e_2 \oplus \ldots \oplus e_m, \tag{2}$$

where $\oplus$ is the row vector connection operator and the dimensions of R_x and R_e denote the number of words in the news and of annotated financial sentiment entities, respectively.

3.3.2. Feature Extraction. For semantic information texts, we used the BiGRU neural network (model structure shown in Figure 3) to handle both forward and reverse text sequences. We extracted the deep text information and then used the financial dictionary to guide attention mechanisms to assign corresponding weights to the extracted feature information. For sentiment information sets, affective information words were encoded using a fully connected network combined with attention mechanisms to obtain affective signals.

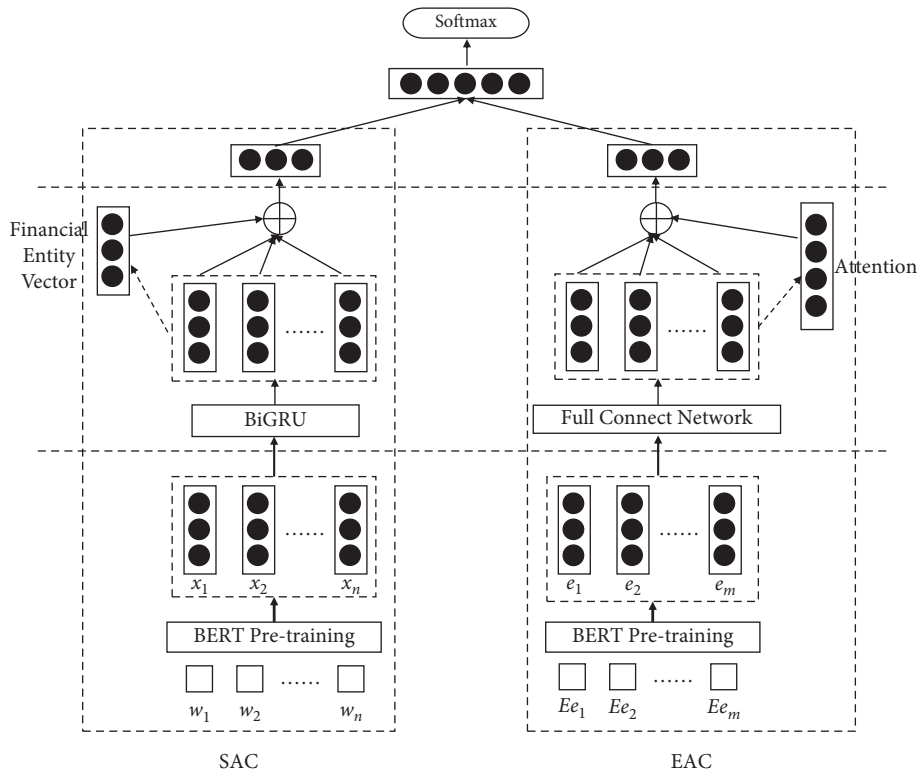

Figure 2: A model framework that combines sentiment dictionaries and attention.

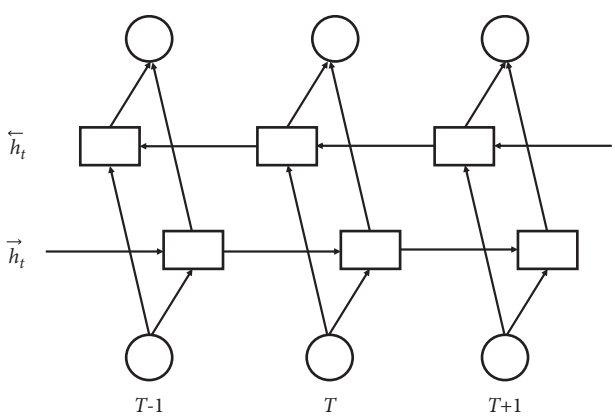

Figure 3: Structure of BiGRU.

The output of the BiGRU information extraction model at time t is composed of the output of the forward and reverse GRU and calculated as follows:

$$\begin{aligned} x_t &= W_e w_t, \quad t \in [1, T], \\ \overrightarrow{h}_t &= \overrightarrow{GRU}(x_t), \quad t \in [1, T], \\ \overleftarrow{h}_t &= \overleftarrow{GRU}(x_t), \quad t \in [1, T], \\ s_t &= \left[\overrightarrow{h}_t, \overleftarrow{h}_t\right], \quad t \in [1, T]. \end{aligned} \tag{3}$$

By combining $\overrightarrow{h}_t$ and $\overleftarrow{h}_t$ to obtain the semantic representation s_t, the forward and reverse semantic information elements are considered in the same position.

Next, we use the financial dictionary to guide attention mechanisms. To improve the accuracy of the sentiment analysis of financial text, we model the relation between sentiment and each word, assigning different weights to the semantic characteristics of the clause using the attention mechanism. In this way, more important words get more attention. Based on the financial entities and BiGRU layer output $H^s = \{h_1^s, h_2^s, \ldots, h_t^s\}$, we obtained vectorized representations as word-level attention. The weight is calculated as follows:

$$\begin{aligned} \alpha_{st} &= \frac{\exp\left(\gamma\left(h_c^s, e^E\right)\right)}{\sum_c \exp\left(\gamma\left(h_c^s, e^E\right)\right)}, \\ \gamma\left(h_c^s, e^E\right) &= \tanh\left(h_c^s \cdot \omega_m^T \cdot e^{E^T} + b_a\right). \end{aligned} \tag{4}$$

The output after BiGRU processing is expressed as $[h_1^s, h_2^s, \ldots, h_c^s]$, where ω_m^T is the weight matrix, b_a is the offset, e^E is the word vector of the financial entity, and α_{st} is the attention weight of the word w_{st} relative to the financial entity e^E. The text features with attention-weighted sentences are represented as follows:

$$o_s = \sum_t a_{st} h_{st}, \tag{5}$$

where o_s is a semantic representation weighted by attention.

3.3.3. Feature Fusion Layer. The main task of the feature fusion layer is to combine the feature vector O^s generated in

SAC and feature vector O^e generated in EAC, to construct the overall sentimental feature vector. To simplify the calculation of the model, we perform feature fusion by row connection, constructing a matrix $O^* = (r_s + r_e) * c$ to generate the feature vector, where r_s and r_e are the number of rows of O^s and O^e, respectively, and c gives the column numbers for O^s and O^e.

3.3.4. Output Layer. We input the sentiment feature vector O^* generated by the feature fusion layer into the SoftMax classifier to obtain the final sentiment classification result predicted by the model as follows:

$$p = \text{softmax}(w_o O^* + b_o), \tag{6}$$

where w_o is the weight coefficient matrix, b_o is the bias matrix, and p is the predicted sentiment label.

3.3.5. Model Training. To use the constructed financial sentiment dictionary that could correspond to the input sentence, we need to construct a sentiment word vector of the same length as the term after the segmentation: Vec_{Att}, initialized as 0. After traversing the words in the input financial text, we set the corresponding position to 1 in the sentiment word vector if they appear in the financial sentiment dictionary. For example, assuming that the input financial text is "Langma cloud business development uncertainty," we first initialize the sentiment word vector $[0, 0, 0, 0, 0]$. After the input sentence, the word "uncertainty" appears in the financial sentiment dictionary, and it is a negative word. Then, we set the word "uncertainty" in the corresponding position of the sentiment word vector to 1, after which the sentiment word vector of the sentence becomes $[0, 0, 0, 0, 1]$.

To employ the financial dictionary shown above as a guiding attention mechanism, we modify the loss function and add $\lambda(\alpha - Vec_{Att})^2$ after the cross-entropy loss. Here, λ is the hyperparameter that determines the importance of sentiment dictionary loss, α is the score of the attention mechanism, and Vec_{Att} is the sentiment dictionary vector. Thus, the attention mechanism score α can fit the financial sentiment word vector for the model to pay more attention to the input financial text—the financial sentiment words. The loss function is as follows:

$$L = -\sum_{i \in D} y_i \log p_i + \lambda(\alpha_{\text{norm}} - Vec_{Att}), \tag{7}$$

where D is the collection of samples, y_i is the true label, and p_i is the prediction result of the model. λ is the hyperparameter that determines the importance of affective dictionary loss and α_{norm} is the average attention score.

We thus use the predicted labels of 1,132,856 news items as the sentiment score in the empirical analysis.

4. Empirical Model

4.1. Sample Selection and Data Sources. Our sample covers all A-share listed firms from 2011 to 2020. Owing to the lag phase of the study, the data time span is nine years (from 2012 to 2020).

We obtain the financial stock trading data from the WIND database. Among them, stock yield is given as weekly data, and the rest, as annual data. Following prior studies [38, 39], we process the original sample as follows: (1) We exclude financial and insurance listed firms; (2) we exclude listed firms with ST or ∗ ST (ST: the company has suffered losses for two consecutive years and is specially treated, ST∗: the company has suffered losses for three consecutive years and warned with delisting.); (3) wexclude listed firms with missing or abnormal data; and (4) we exclude listed firms with less than 15 weekly yield data.

We obtain data regarding Internet media news from the GuoTai'an (CASMAR) database. We perform positive and negative analyses of each report using sentiment analysis technology and assign sentiment scores. We then calculate the sum of the number of relevant news reports during the research period, average level of sentiment scores, and sentiment scores weighted by the number of news reports.

4.2. Econometric Model and Variables. To study the relation between diversification and future stock price crash risk, we construct a multiple regression model as follows:

$$\begin{aligned}\text{CrashRisk}_{i,t} = {} & \beta_0 \text{Cons} + \beta_1 \text{NewsSentiment}_{i,t-1} + \beta_2 \text{Size}_{i,t-1} \\ & + \beta_3 \text{Level}_{i,t-1} + \beta_4 \text{ROA}_{i,t-1} + \beta_5 \text{Ret}_{i,t-1} \\ & + \beta_6 \text{Sigma}_{i,t-1} + \sum \text{Year} + \sum \text{Firm} + \varepsilon_{i,t}.\end{aligned} \tag{8}$$

In the model, the explained variable CrashRisk represents the risk of a crash in individual stocks. NewsSentiment is the core explanatory variable, indicating the calculated sentimental score for the individual stock news report. Size denotes the size of the enterprise, Level represents the financial leverage of the company, *ROA* is the return on equity of the company, *Ret* is the average of the enterprise-specific weekly rate, and Sigma is the standard deviation of the enterprise-specific weekly rate. Year and Firm are time and firm fixed effects, respectively. Here, we focus on the coefficient β_1. If β_1 is significantly positive, then there is a positive relation between the news reporting sentiment and risk of a stock price crash. Conversely, if β_1 is significantly negative, then there is a negative relation between the news reporting sentiment and risk of a stock price crash. The variables are introduced in Table 3 and elaborated as follows:

4.2.1. Explained Variables. Based on the methods of Jin and Myers [33] and Xu et al. [40], our study employs three approaches to measure the risk of a stock price crash. The specific algorithm is as follows:

The unexplained weekly yield of individual stocks in the market is calculated using the following model:

$$R_{i,t} = R_{m,t-2} + R_{m,t-1} + R_{m,t} + R_{m,t+1} + R_{m,t+2} + \varepsilon_{i,t}, \tag{9}$$

where $R_{i,t}$ represents the weekly yield of stock i in week t. $R_{m,t}$ is the weighted average of the weekly yield of week t. $\varepsilon_{i,t}$

Table 3: Variables and definitions.

	Indicator	Definition
Dependent variables	CRASH	Used to measure the risk of a crash: 1, 0 indicator
	NCSKEW	Used to measure the risk of a crash: negative return bias coefficient
	DUVOL	Used to measure the risk of a crash: the earnings fluctuation ratio
Independent variables	newSenti newPos newNeg	News coverage' sentiment
	anaSenti	Analysts' sentiment
Control variables	Size	The natural logarithm of the firm's market value
	Level	Firm's leverage, equal to the ratio of the firm's total liabilities to total assets
	ROA	The ratio of net profit to total assets
	Ret	The average value of the firm's annual weekly rate of return
	Sigma	The standard deviation of the firm's annual weekly rate of return
	Year	Yearly dummy variable
	Firm	Firm dummy variable

is the residual in equation (2), which represents the weekly return of stocks not explained in the market. Because $\epsilon_{i,t}$ is highly biased, we use $W_{i,t} = \ln(1 + \varepsilon_{i,t})$ to represent stock-specific weekly yields. Based on $W_{i,t}$, we measure the risk of a stock price crash using three indicators—(CRASH), a negative return bias coefficient (NSCKEW), and the earnings fluctuation ratio (DUVOL).

CRASH is calculated as follows:

$$\mathrm{CRASH}_{i,t} = 1\left[\exists t, W_{i,t} \leq \mathrm{Average}\left(W_{i,t}\right) - 3.09\sigma_{i,t}\right]. \quad (10)$$

$\mathrm{CRASH}_{i,t}$ equals 1 if a firm experiences one or more firm-specific weekly returns $W_{i,t}$ falling 3.09 standard deviations below the mean firm-specific weekly return, and 0 otherwise.

NSCKEW is calculated as follows:

$$\mathrm{NCSKEW}_{i,t} = \frac{-\left[n(n-1)^{3/2}\sum W_{i,t}^3\right]}{\left[(n-1)(n-2)\left(\sum W_{i,t}^3\right)^{3/2}\right]}, \quad (11)$$

where n represents the number of stock i in year t. The coefficient of the negative return bias is a positive measure of the risk of a stock price crash. Thus, the greater the coefficient is, the higher the possibility of a stock price crash.

DUVOL is calculated as follows:

$$\mathrm{DUVOL}_{i,t} = \log\left\{\frac{\left[(n_u - 1)\sum_{\mathrm{DOWN}} W_{i,t}^2\right]}{\left[(n_d - 1)\sum_{\mathrm{UP}} W_{i,t}^2\right]}\right\}. \quad (12)$$

The core explanatory variable in our study is a quantitatively weighted news reporting sentiment propensity, which is calculated as follows:

4.2.2. Explanatory Variables. The core explanatory variable in this study is a quantitatively weighted news reporting sentimental propensity, which is calculated as follows:

$$\mathrm{newSenti}_{i,T} = \frac{\mathrm{NewsCount}_{i,t} * \mathrm{SentimentScore}_{i,t}}{\sum \mathrm{NewsCount}_{i,t}}, \quad (13)$$

where $\mathrm{newSenti}_{i,T}$ represents the media report sentiment tone of stock in year T. $\mathrm{NewsCount}_{i,t}$ represents the number of news items regarding stock i in year T. $\mathrm{SentimentScore}_{i,t}$ represents the average media reporting sentiment scores of trading day t of stock i in year T, each calculated by our BERT-DCA model. Regarding the number of news, the higher it is, the more likely the investors will read the news. Thus, the probability that the reported sentiments are transmitted to investors is also higher. To examine how different types of Internet news sentiment work, we construct both positive and negative news coverage sentiment indicators.

$$\mathrm{newPos}_{i,T} = \frac{\mathrm{PosNewsCount}_{i,t} * \mathrm{PosSentimentScore}_{i,t}}{\sum \mathrm{PosNewsCount}_{i,t}},$$

$$\mathrm{newNeg}_{i,T} = \frac{\mathrm{NegNewsCount}_{i,t} * \mathrm{NegSentimentScore}_{i,t}}{\sum \mathrm{NegNewsCount}_{i,t}}. \quad (14)$$

To study the impact of market differences on the risk of a stock price crash, we use analysts' rating data to calculate their sentiments. First, we grade analysts on five points: +2, +1, 0, −1, and −2, indicating buy, overweight, neutral, reduction, and sell, respectively. We then calculate the total score of the year, divide it by the rating number, and finally standardize it using ~$N(0,1)$, given as *Ana_senti*.

4.2.3. Control Variables. Following Jin and Myers [33], the control variables are defined as follows.

Enterprise size (*Size*) is expressed as the natural logarithm of the enterprise market value.

Operating leverage (*Level*) is the enterprise asset–liability ratio.

Compensation rate of corporate total assets (*ROA*) is an indicator used to measure corporate profitability.

Previous value of negative return bias coefficient/fluctuation ratio is used to control the impact of the lag phase of the risk of a stock price crash.

Stock-specific weekly earnings annual average (*Ret*) reflects the average level of stock yield.

Weekly earnings volatility (*Sigma*) reflects the volatility levels of stock-specific weekly earnings.

Table 4: Baseline regression.

	(1) CRASH	(2) CRASH	(3) NCSKEW	(4) NCSKEW	(5) DUVOL	(6) DUVOL
L.newSenti	0.087***	0.064**	0.395***	0.190**	0.203***	0.103*
	(0.031)	(0.032)	(0.092)	(0.094)	(0.062)	(0.060)
L.CRASH		−0.147***				
		(0.009)				
L.NCSKEW				−0.096***		
				(0.009)		
L.DUVOL						−0.106***
						(0.008)
L.ret		0.957**		8.770***		6.232***
		(0.410)		(0.842)		(0.584)
L.sigma		0.594***		1.039**		1.192***
		(0.195)		(0.441)		(0.299)
L.roa		0.360		1.339***		0.860***
		(0.224)		(0.459)		(0.307)
L.level		−0.012		−0.130**		−0.113***
		(0.033)		(0.059)		(0.039)
L.size		0.000		0.000*		0.000
		(0.000)		(0.000)		(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	18,775	17,267	18,775	17,267	18,775	17,267
R^2	0.000	0.035	0.001	0.060	0.001	0.065

This table reports baseline regression estimates of stock crash risk on the quantitatively weighted news coverage sentiment. The sample of CRASH is used for columns (1)-(2), the sample of NCSKEW is used for columns (3)-(4), and that of DUVOL is used columns (5)-(6). Columns (1), (3), and (5) only include the news coverage sentiment; columns (2), (4), and (6) control for lagged crash risk and firm characteristic; year and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

5. Empirical Analysis

5.1. News Sentiment and the Risk of a Stock Price Crash. Table 4 shows the analysis results for the relation between the media sentiment and future stock price crash risk. Columns 1, 3, and 5 in Table 4 are the effects of the sentiment weighted by the number of news items (*newSenti*) on the risk of a future stock price crash where control variables are not included. We found a significant positive effect of CRASH (0.087), NCSKEW (0.395), and DUVOL (0.203). Columns 2, 4, and 6 show the effect of sentiment (*newSenti*) on the future stock price crash risk after adding all control variables. Similarly, we find a significant positive effect on CRASH (0.064), NCSKEW (0.190), and DUVOL (0.103). Although the coefficient decreases after including control variables, they are still economically and statistically significant. Thus, the more positive the average media sentiment is, the higher the future stock price crash risk, or the more negative the current average news sentiment is, the lower the risk of a future stock price crash. These findings support *H1a* but not *H1b*.

Regarding the control variables, we observe a negative effect of firm financial leverage on the risk of a future stock price crash, implying that the latter risk is higher in firms with lower financial leverage—the smaller the size of the firm, the higher the risk. In addition, we find that a firm's stock return (*ROA*) is significantly and negatively related to the risk of a future stock price crash, implying that the better the performance of a firm, the less likely it is to have a stock price crash in future. The effects of the other control variables on future stock price crash risk are not robust.

According to the results of the baseline regression, media sentiment is positively related to the future stock price crash risk. We replace average media sentiment in the baseline regression with media coverage positive and negative sentiment indicators to examine hypothesis *H2*. The results are shown in Table 5.

Columns 1, 2, and 3 in Panel A indicate that the effect of positive sentiment is significant at the 1% level, whereas Columns 4, 5, and 6 indicate that the effect of negative sentiment is insignificant. The regression results suggest that positive media sentiment plays a dominant role in China; the more positive the media sentiment, the higher the future stock price crash risk. Under information asymmetry, uninformed investors receive more positive information and irrational investors develop an overvaluation of stock prices [2, 14]. The negative sentiment appears to curb future crash risk, but the effect is insignificant.

Indeed, investors react more strongly to negative news [31]. Negative news causes retail investors to sell and increases the risk of a future stock price crash [32]. However, our findings indicate that negative news in the previous one

Table 5: Positive sentiment and negative sentiments of news coverage.

	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
Panel A: one lag period						
L.newPos	0.135***	0.516***	0.323***			
	(0.045)	(0.187)	(0.125)			
L.newNeg				0.033	0.087	0.015
				(0.073)	(0.162)	(0.110)
L.CRASH	−0.152***			−0.151***		
	(0.009)			(0.009)		
L.NCSKEW		−0.102***			−0.107***	
		(0.009)			(0.009)	
L.DUVOL			−0.111***			−0.116***
			(0.009)			(0.009)
L.ret	1.060**	9.014***	6.415***	1.016**	9.305***	6.560***
	(0.426)	(0.869)	(0.606)	(0.431)	(0.888)	(0.614)
L.sigma	0.618***	1.204***	1.261***	0.545***	1.059**	1.183***
	(0.204)	(0.455)	(0.310)	(0.203)	(0.459)	(0.312)
L.roa	0.371	1.388***	0.877***	0.425*	1.427***	0.812**
	(0.236)	(0.489)	(0.321)	(0.235)	(0.485)	(0.326)
L.level	−0.016	−0.111*	−0.108***	−0.004	−0.147**	−0.142***
	(0.035)	(0.059)	(0.040)	(0.037)	(0.063)	(0.042)
L.size	0.000	0.000*	0.000	0.000	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fix effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	16,267	16,267	16,267	15,966	15,966	15,966
R^2	0.036	0.060	0.067	0.036	0.062	0.068
Panel B: same period						
newPos	−0.068	−0.023	−0.010			
	(0.088)	(0.187)	(0.129)			
newNeg				−0.185**	−0.427***	−0.303***
				(0.077)	(0.159)	(0.111)
L.CRASH	−0.161***			−0.161***		
	(0.009)			(0.009)		
L.NCSKEW		−0.109***			−0.110***	
		(0.009)			(0.009)	
L.DUVOL			−0.113***			−0.116***
			(0.009)			(0.009)
L.ret	0.662	5.425***	3.671***	0.570	5.596***	3.864***
	(0.417)	(0.888)	(0.630)	(0.425)	(0.908)	(0.640)
L.sigma	0.566***	0.138	0.219	0.556***	0.105	0.311
	(0.202)	(0.466)	(0.322)	(0.201)	(0.475)	(0.326)
L.roa	0.647***	1.765***	1.094***	0.489**	1.272***	0.822**
	(0.221)	(0.461)	(0.316)	(0.214)	(0.467)	(0.321)
L.level	−0.048	−0.112*	−0.108**	−0.049	−0.116*	−0.115***
	(0.036)	(0.066)	(0.044)	(0.036)	(0.065)	(0.044)
L.size	−0.000	0.000	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fix effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	16,267	16,267	16,267	15,966	15,966	15,966
R^2	0.041	0.066	0.072	0.037	0.064	0.070

This table reports regression estimates of stock crash risk on the news coverage positive and negative sentiment indicators. Panel A is one year lag; panel B is the same year; year and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 6: Quarterly crash risk for different future periods.

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH	(5) CRASH	(6) CRASH	(7) CRASH	(8) CRASH
newPos	−0.035							
	(0.039)							
L.newPos		0.116***						
		(0.039)						
L2.newPos			0.082**					
			(0.039)					
L3.newPos				0.047				
				(0.039)				
newNeg					−0.164***			
					(0.036)			
L.newNeg						0.046		
						(0.036)		
L2.newNeg							0.042	
							(0.036)	
L3.newNeg								−0.048
								(0.036)
L.CRASH	−0.052***	−0.053***	−0.055***	−0.052***	−0.052***	−0.053***	−0.052***	−0.053***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
L.ret	1.523***	1.824***	2.339***	2.999***	1.709***	1.917***	2.418***	2.833***
	(0.479)	(0.484)	(0.540)	(0.565)	(0.476)	(0.478)	(0.533)	(0.540)
L.sigma	1.734***	1.633***	1.807***	2.052***	1.698***	1.617***	2.066***	1.916***
	(0.253)	(0.260)	(0.282)	(0.283)	(0.260)	(0.256)	(0.276)	(0.280)
L.roa	−0.070	−0.132***	−0.194***	−0.141***	−0.095*	−0.143***	−0.134***	−0.155***
	(0.052)	(0.051)	(0.053)	(0.052)	(0.052)	(0.051)	(0.052)	(0.053)
L.level	−0.038**	−0.037**	−0.038*	−0.034*	−0.029	−0.030	−0.038*	−0.009
	(0.019)	(0.018)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)
L.size	0.000	−0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects								
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	51,110	51,110	51,110	51,110	51,919	51,919	51,919	51,919
R^2	0.040	0.039	0.039	0.038	0.037	0.038	0.039	0.038

This table reports regression estimates of quarterly stock crash risk on the news coverage positive and negative sentiment indicators. Columns (1) to (4) are positive indicators. Columns (5) to (8) are negative indicators; quarter and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 7: Two stages OLS regression.

	First stage	Second stage		
	(1) Newsenti	(2) CRASH	(3) NCSKEW	(4) DUVOL
L.newSenti		0.074***	0.510**	0.313**
		(0.028)	(0.253)	(0.157)
L.newSentiInd	0.873***			
	(0.022)			
L.newSentiPro	0.747***			
	(0.041)			
Controls	Yes	Yes	Yes	Yes
Cragg-Donald Wald F	185.966***			
Sargan chi (p)		0.257 (0.612)	0.571 (0.450)	1.466 (0.226)
N	16,845	16,845	16,845	16,845
R^2	0.212	0.035	0.059	0.064

This table reports regression estimates of stock crash risk on the news coverage sentiment indicators two stage OLS. Columns (1) is first stage. Columns (2) to (4) are second stage; year and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 8: Regression results for corporate insider trading.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti	0.030	−0.394	−0.154	0.103***	0.336***	0.119**
	(0.168)	(0.333)	(0.224)	(0.037)	(0.114)	(0.059)
L.CRASH	−0.144***			−0.185***		
	(0.010)			(0.033)		
L.NCSKEW		−0.088***			−0.096***	
		(0.034)			(0.009)	
L.DUVOL			−0.072**			−0.109***
			(0.032)			(0.009)
L.ret	1.570	10.925***	7.660***	0.933**	8.500***	6.077***
	(1.382)	(2.656)	(1.897)	(0.454)	(0.954)	(0.661)
L.sigma	1.427*	3.266**	2.124*	0.541**	0.707	1.049***
	(0.744)	(1.595)	(1.135)	(0.214)	(0.485)	(0.326)
L.roa	−0.717	0.484	0.712	0.453*	1.598***	1.016***
	(0.880)	(1.754)	(1.204)	(0.235)	(0.498)	(0.336)
L.level	−0.036	0.014	−0.035	0.020	−0.120*	−0.104**
	(0.112)	(0.214)	(0.150)	(0.036)	(0.064)	(0.041)
L.size	−0.000	−0.000	−0.000*	0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,488	5,488	5,488	5,884	5,884	5,884
R^2	0.035	0.064	0.069	0.043	0.036	0.055

This table reports panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of high insider trading groups and low insider trading groups. The total sample is divided into two subsamples: lower and higher groups, based on 30% and 70% quartiles of insiders' net stock sales, respectively. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 9: Regression results for information disclosure quality.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti	0.051	0.026	−0.093	0.114***	0.384**	0.196**
	(0.106)	(0.222)	(0.144)	(0.043)	(0.179)	(0.098)
L.CRASH	−0.114***			−0.162***		
	(0.019)			(0.019)		
L.NCSKEW		−0.098***			−0.111***	
		(0.021)			(0.015)	
L.DUVOL			−0.101***			−0.124***
			(0.020)			(0.016)
L.ret	2.489***	11.948***	8.111***	0.494	5.299***	4.534***
	(0.939)	(2.231)	(1.424)	(0.853)	(1.451)	(1.117)
L.sigma	1.725***	1.739*	1.502**	0.239	1.582**	1.326**
	(0.411)	(1.045)	(0.662)	(0.437)	(0.744)	(0.579)
L.roa	−0.430	−0.536	0.197	0.768*	1.134*	0.586
	(0.544)	(1.349)	(0.864)	(0.405)	(0.665)	(0.487)
L.level	−0.141***	0.037	0.040	−0.025	−0.218**	−0.205***
	(0.042)	(0.112)	(0.069)	(0.059)	(0.102)	(0.076)
L.size	0.000	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,488	5,488	5,488	5,884	5,884	5,884
R^2	0.038	0.064	0.070	0.044	0.080	0.079

This table reports panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of high information disclosure quality groups and low information disclosure quality groups. The total sample is divided into two subsamples: lower and higher groups, based on 30% and 70% quartiles of KV index, respectively. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 10: Regression results for analysts' coverage.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti	0.129**	0.543**	0.413**	0.029	0.132	0.147
	(0.058)	(0.221)	(0.167)	(0.078)	(0.220)	(0.146)
L.CRASH	−0.200***			−0.179***		
	(0.029)			(0.012)		
L.NCSKEW		−0.163***			−0.102***	
		(0.018)			(0.022)	
L.DUVOL			−0.156***			−0.121***
			(0.019)			(0.021)
L.ret	2.276	6.842***	6.149***	0.841	3.826*	2.842*
	(1.427)	(1.432)	(1.104)	(0.531)	(2.198)	(1.504)
L.sigma	1.788***	0.335	0.675	0.417	0.063	0.920
	(0.600)	(0.839)	(0.641)	(0.274)	(1.060)	(0.721)
L.roa	0.159	2.087***	0.600	0.480*	0.598	0.891
	(0.783)	(0.760)	(0.538)	(0.284)	(1.204)	(0.798)
L.level	0.029	−0.158	−0.131	−0.030	−0.051	−0.031
	(0.093)	(0.134)	(0.103)	(0.041)	(0.088)	(0.060)
L.size	0.000*	0.000	0.000**	0.000	0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	4618	4618	4618	4569	4569	4569
R^2	0.066	0.073	0.069	0.078	0.081	0.086

This table reports panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of low analysts' attention groups and high analysts' attention groups. We used the total number of analysts coverage of firms to measure analysts' attention. We used the 30% and 70% quartiles of analysts' attention as the cut-off, and the firms were divided into low and high attention groups. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW and DUVOL, respectively; column (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 11: Regression results for different institutional holding groups.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti	0.092**	0.481***	0.358***	0.018	0.037	−0.027
	(0.044)	(0.176)	(0.124)	(0.094)	(0.220)	(0.144)
L.CRASH	−0.172***			−0.204***		
	(0.016)			(0.022)		
L.NCSKEW		−0.131***			−0.161***	
		(0.015)			(0.020)	
L.DUVOL			−0.170***			−0.182***
			(0.014)			(0.019)
L.ret	0.933	6.633***	5.416***	0.316	2.351	2.020
	(0.720)	(1.339)	(0.959)	(1.001)	(2.192)	(1.487)
L.sigma	0.697**	0.236	0.744	0.632	0.272	0.755
	(0.343)	(0.726)	(0.527)	(0.447)	(1.023)	(0.678)
L.roa	0.183	0.638	0.310	0.423	0.861	0.850
	(0.376)	(0.706)	(0.537)	(0.538)	(1.256)	(0.784)
L.level	−0.062	−0.072	−0.087*	−0.100	−0.346**	−0.181*
	(0.049)	(0.070)	(0.049)	(0.070)	(0.171)	(0.109)
L.size	0.000	0.000***	0.000***	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	4,734	4,734	4,734	6,513	6,513	6,513
R^2	0.046	0.071	0.087	0.057	0.080	0.092

This table reports panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of low institutional shareholding groups and high institutional shareholding groups. We used the 30% and 70% quartiles of the institutional shareholding as the cut-off point, and the firms were divided into low and high shareholding groups. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 12: Regression results for different investor sentiment.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti	−0.011	−0.063	−0.097	0.176**	0.441**	0.254**
	(0.109)	(0.231)	(0.151)	(0.073)	(0.196)	(0.128)
L.CRASH	−0.178***			−0.173***		
	(0.019)			(0.016)		
L.NCSKEW		−0.144***			−0.104***	
		(0.019)			(0.018)	
L.DUVOL			−0.133***			−0.126***
			(0.019)			(0.017)
L.ret	2.540***	7.085***	4.014***	2.426***	6.721***	4.536***
	(0.677)	(1.893)	(1.318)	(0.759)	(1.778)	(1.205)
L.sigma	0.665	1.373	0.977	0.789**	0.826	0.019
	(0.437)	(0.929)	(0.606)	(0.371)	(0.925)	(0.634)
L.roa	0.755	1.529	1.205*	0.554	2.048**	1.666**
	(0.605)	(0.981)	(0.617)	(0.409)	(0.995)	(0.699)
L.level	0.036	−0.196*	−0.102	−0.003	−0.089	−0.087
	(0.067)	(0.106)	(0.066)	(0.055)	(0.128)	(0.088)
L.size	0.000	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	4,881	4,881	4,881	5,863	5,863	5,863
R^2	0.047	0.078	0.085	0.050	0.071	0.083

This table reports panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of pessimistic investor groups and optimistic investor groups. We used the 30% and 70% quartiles of the investor sentiment as the cut-off point, and the firms were divided into low and high shareholding groups. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 13: Regression of adding analyst and media coverage sentiment crossterms.

	(1) CRASH	(2) NCSKEW	(3) DUVOL
L.newSenti	0.186*	0.360**	0.266
	(0.109)	(0.171)	(0.158)
L.anaSenti	0.039***	0.057**	0.049***
	(0.011)	(0.024)	(0.016)
L.newSenti#L.anaSenti	−0.247*	−0.172*	−0.156*
	(0.145)	(0.100)	(0.092)
L.CRASH	−0.151***		
	(0.009)		
L.NCSKEW		−0.102***	
		(0.009)	
L.DUVOL			−0.111***
			(0.009)
L.ret	0.942**	8.677***	6.188***
	(0.426)	(0.867)	(0.603)
L.sigma	0.524**	0.874*	1.120***
	(0.206)	(0.460)	(0.315)
L.roa	0.285	1.286***	0.813**
	(0.231)	(0.484)	(0.325)
L.level	0.006	−0.141**	−0.109***
	(0.036)	(0.062)	(0.041)
L.size	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)
Fixed effects:			
Year dummy	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes
N	15,753	15,753	15,753
R^2	0.037	0.064	0.069

This table reports panel estimates of stock crash risk on the interaction between the news coverage sentiment and the analysis report sentiment. The dependent variables in Columns (1), (2), and (3) are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

year does not increase the risk of a future stock price crash. A reason may be that investors are overly sensitive to negative news, particularly in markets with a high proportion of irrational investors, such as China. When negative news breaks, investors panic and quickly sell their stocks, resulting in a significant drop in the stock price below its fundamental value, which means the occurrence of the price crash in the current term rather than the future. Thus, negative news coverage can be hypothesized to increase the current stock crash risk, whereas positive media coverage decreases such a risk. The results are represented in Table 5, Panel B. It shows that the effects of negative news in the current period is significant, confirming our analysis that the more negative the news, the greater the risk of a crash in the current period. Meanwhile, the effects of positive media coverage are insignificant, indicating that positive news suppresses the risk of a crash in the current period. However, because investors are less sensitive to positive than negative news, their impact is not significant.

To investigate the robustness of the impact of positive and negative news, we considered quarterly level crash risk regressions that included current, prior one period to prior three period indicators for positive and negative news, respectively. The results are shown in Table 6. Overall, the quarterly regression results are consistent with the annual regression results. Positive news reduces the risk of a stock price crash in the current period (−0.035); however, the effect is not statistically significant. Columns 2–4 show that positive news significantly increases the risk of a stock price crash in the future period, consistent with the annual regression. Negative media coverage increases the current period crash risk (−0.164) and had a significant effect. Columns 6–8 reveal that negative media coverage reduces the future stock price crash risk, but the suppression effect is insignificant except for the previous period. These results confirm *H2a* but not *H2b*.

5.2. Endogeneity. The relation between media coverage and stock returns is endogenous. The reverse causality, as media coverage is more likely to focus on stocks with higher returns; also, there may be control variables that we are unaware of, resulting in the omitted variables problem.

Following Xu et al. [41] and Ertugrul et al. [42], we select industry-level news sentiment means (*newSentiInd*) but exclude the company and province levels (*newSentiPro*) as the instrument variables for firms' media sentiment. We presume that other publicly traded firms in the same industry or province would face similar industry characteristics and external environments; thus, their media coverage may have a certain correlation. Furthermore, there is no evidence that media coverage of other publicly traded firms in the same industry or province will influence a firm's stock trading behavior, which satisfies the exclusion restriction to some extent.

Table 7 shows the regression results. The coefficients of the *newSentiInd* and *newSentiPro* variables are significantly positive in Column 1, indicating that the higher the media sentiment of listed firms in the industry and province, the higher the mean value of the sentiment of the listed firms. The Cragg–Donald F statistic equals 185.966, which is much larger than the critical value, and this statistic rejects the hypothesis that the instrumental variables are weak at the 1% level. The results of the second stage regression in Columns 2, 3, and 4 show that none of the values of the Sargan statistic reject the original hypothesis of instrumental variable exogeneity. The results of *newSenti* continue to be significantly positive, which is in line with the results of the main regression.

5.3. Channels between News Coverage and Crash Risk. Media sentiment affects the risk of a future stock price crash via two mechanisms. The first is through the investor sentiment, which, in turn, affects stock crash risk. The second is that media coverage serves as an information intermediary, conveying true or false information on listed firms; investors influence the crash risk by interpreting the information they receive.

Table 14: Robust test: baseline regression.

	(1) CRASH	(2) CRASH	(3) NCSKEW	(4) NCSKEW	(5) DUVOL	(6) DUVOL
L.newSenti2	0.100***	0.078**	0.561***	0.221**	0.317***	0.151**
	(0.037)	(0.038)	(0.091)	(0.106)	(0.060)	(0.071)
L.CRASH		−0.145***		−0.092***		
		(0.008)		(0.008)		
L.NCSKEW						−0.101***
						(0.008)
L.DUVOL				8.451***		6.011***
				(0.814)		(0.565)
L.ret		0.948**		0.794*		1.015***
		(0.391)		(0.427)		(0.288)
L.sigma		−0.589***		1.303***		0.734**
		(0.188)		(0.431)		(0.292)
L.roa		0.435**		−0.142**		−0.114***
		(0.210)		(0.057)		(0.037)
L.level		0.019		0.000*		0.000
		(0.031)		(0.000)		(0.000)
L.size		0.000		0.000*		0.000
		(0.000)		(0.000)		(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	20,107	18,456	20,107	18,456	20,107	18,456
R^2	0.000	0.037	0.002	0.062	0.002	0.068

This table reports robust baseline regression estimates of stock crash risk on the quantitatively weighted news coverage sentiment. The sample of CRASH is used for columns (1)-(2), the sample of NCSKEW is used for columns (3)-(4), and that of DUVOL is used columns (5)-(6). Columns (1), (3), and (5) only include the news coverage sentiment. Columns (2), (4), and (6) control for lagged crash risk and firm characteristic; year and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 15: Robust test: positive sentiment and negative sentiments of news coverage.

	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
Panel A: one lag period						
L.newPos2	0.161***	0.331**	0.228**			
	(0.061)	(0.164)	(0.113)			
L.newNeg2				0.066	0.180	0.045
				(0.068)	(0.154)	(0.105)
L.CRASH	−0.147***			−0.147***		
	(0.008)			(0.009)		
L.NCSKEW		−0.095***			−0.099***	
		(0.008)			(0.009)	
L.DUVOL			−0.104***			−0.107***
			(0.008)			(0.008)
L.ret	1.058***	8.719***	6.152***	0.896**	8.770***	6.304***
	(0.400)	(0.830)	(0.577)	(0.404)	(0.844)	(0.585)
L.sigma	−0.627***	0.937**	1.058***	−0.550***	0.966**	1.160***
	(0.194)	(0.439)	(0.298)	(0.192)	(0.440)	(0.298)
L.roa	0.417*	1.291***	0.773**	0.462**	1.487***	0.845***
	(0.220)	(0.454)	(0.301)	(0.218)	(0.452)	(0.307)
L.level	0.018	−0.116**	−0.103***	0.010	−0.163***	−0.141***
	(0.032)	(0.057)	(0.038)	(0.034)	(0.060)	(0.040)
L.size	0.000	0.000*	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fix effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	17,363	17,363	17,363	16,276	16,276	16,276
R^2	0.036	0.060	0.067	0.036	0.062	0.068
Panel B: same period						
newPos2	−0.065	0.006	0.042			
	(0.085)	(0.180)	(0.123)			
newNeg2				−0.303***	−0.739***	−0.531***
				(0.080)	(0.154)	(0.108)
L.CRASH	−0.153***			−0.154***		
	(0.009)			(0.009)		
L.NCSKEW		−0.102***			−0.105***	
		(0.009)			(0.009)	
L.DUVOL			−0.108***			−0.108***
			(0.009)			(0.009)
L.ret	0.363	4.913***	3.543***	0.423	5.466***	3.870***
	(0.395)	(0.844)	(0.594)	(0.407)	(0.863)	(0.610)
L.sigma	−0.508***	0.146	0.299	−0.519***	0.104	0.297
	(0.190)	(0.446)	(0.307)	(0.192)	(0.448)	(0.310)
L.roa	0.661***	1.581***	0.894***	0.524**	1.468***	0.919***
	(0.207)	(0.428)	(0.296)	(0.207)	(0.439)	(0.304)
L.level	0.053	−0.110*	−0.104**	0.070**	−0.083	−0.083**
	(0.033)	(0.060)	(0.041)	(0.032)	(0.059)	(0.040)
L.size	−0.000	0.000	0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fix effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	17,363	17,363	17,363	16,276	16,276	16,276
R^2	0.041	0.066	0.072	0.037	0.064	0.070

This table reports robust regression estimates of stock crash risk on the news coverage positive and negative sentiment indicators. Panel A is one year lag; panel B is the same year; year and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 16: Robust test: quarterly crash risk for different future periods.

	(1) CRASH	(2) CRASH	(3) CRASH	(4) CRASH	(5) CRASH	(6) CRASH	(7) CRASH	(8) CRASH
newPos2	−0.049							
	(0.038)							
L.newPos2		0.096**						
		(0.038)						
L2.newPos2			0.084**					
			(0.039)					
L3.newPos2				0.025				
				(0.038)				
newNeg2					−0.248***			
					(0.035)			
L.newNeg2						0.034		
						(0.033)		
L2.newNeg2							−0.015	
							(0.035)	
L3.newNeg2								0.027
								(0.033)
L.CRASH	−0.048***	−0.049***	−0.047***	−0.047***	−0.049***	−0.049***	−0.048***	−0.045***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
L.ret	1.921***	1.909***	2.445***	3.096***	1.837***	1.773***	2.562***	3.184***
	(0.447)	(0.450)	(0.502)	(0.508)	(0.457)	(0.458)	(0.505)	(0.525)
L.sigma	−1.686***	−1.464***	−2.182***	−2.174***	−1.780***	−1.411***	−1.931***	−2.287***
	(0.237)	(0.234)	(0.259)	(0.262)	(0.239)	(0.239)	(0.263)	(0.264)
L.roa	−0.091**	−0.123***	−0.122***	−0.121***	−0.062	−0.124***	−0.141***	−0.118**
	(0.046)	(0.046)	(0.047)	(0.046)	(0.047)	(0.046)	(0.049)	(0.047)
L.level	−0.037**	−0.034*	−0.029*	−0.018	−0.036**	−0.045***	−0.038**	−0.029
	(0.016)	(0.018)	(0.017)	(0.019)	(0.017)	(0.017)	(0.017)	(0.018)
L.size	0.000	−0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:								
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	58,530	58,530	58,530	58,530	59,748	59,748	59,748	59,748
R^2	0.038	0.037	0.039	0.038	0.040	0.039	0.039	0.038

This table reports robust regression estimates of stock crash risk on the news coverage sentiment indicators two stage OLS. Column (1) is the first stage. Columns (2) to (4) are the second stage; year and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 17: Robust test: two stages OLS regression.

	First stage	Second stage		
	(1) newsenti	(2) CRASH	(3) NCSKEW	(4) DUVOL
L.newSenti2		0.092**	0.994*	0.419*
		(0.045)	(0.456)	(0.246)
L.newSentiInd	0.494***			
	(0.020)			
L.newSentiPro	0.476***			
	(0.037)			
Controls	Yes	Yes	Yes	Yes
Cragg-Donald Wald F	185.966***			
Sargan chi (p)		0.121 (0.788)	0.004 (0.947)	0.254 (0.614)
N	16,845	16,845	16,845	16,845
R^2	0.212	0.035	0.059	0.064

Table 18: Robust test: regression results for corporate insider trading.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti2	0.011	−0.394	−0.154	0.097**	0.336***	0.119**
	(0.052)	(0.333)	(0.224)	(0.048)	(0.114)	(0.059)
L.CRASH	−0.143***			−0.174***		
	(0.009)			(0.031)		
L.NCSKEW		−0.091***			−0.094***	
		(0.032)			(0.009)	
L.DUVOL			−0.084***			−0.104***
			(0.030)			(0.009)
L.ret	1.834	10.422***	7.613***	1.020**	8.353***	5.892***
	(1.346)	(2.642)	(1.858)	(0.429)	(0.917)	(0.638)
L.sigma	−1.305*	2.975*	2.061*	−0.586***	0.550	0.891***
	(0.721)	(1.559)	(1.090)	(0.205)	(0.467)	(0.313)
L.roa	−0.316	1.063	0.783	0.516**	1.509***	0.876***
	(0.801)	(1.615)	(1.111)	(0.218)	(0.465)	(0.317)
L.level	−0.027	−0.058	−0.020	0.028	−0.138**	−0.108***
	(0.108)	(0.208)	(0.144)	(0.033)	(0.062)	(0.040)
L.size	−0.000	−0.000	−0.000**	0.000	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,488	5,488	5,488	5,884	5,884	5,884
R^2	0.035	0.065	0.071	0.043	0.047	0.067

This table reports robust panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of high insider trading groups and low insider trading groups. The total sample is divided into two subsamples: lower and higher groups, based on 30% and 70% quartiles of insiders' net stock sales, respectively. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 19: Robust test: regression results for information disclosure quality.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti2	0.011	0.026	−0.093	0.122***	0.384**	0.196**
	(0.098)	(0.222)	(0.144)	(0.039)	(0.179)	(0.098)
L.CRASH	−0.120***			−0.157***		
	(0.017)			(0.018)		
L.NCSKEW		−0.094***			−0.101***	
		(0.020)			(0.014)	
L.DUVOL			−0.100***			−0.117***
			(0.018)			(0.015)
L.ret	2.396***	10.914***	7.517***	0.510	5.451***	4.603***
	(0.884)	(2.111)	(1.351)	(0.787)	(1.366)	(1.061)
L.sigma	−1.702***	1.233	1.136*	−0.165	1.549**	1.347**
	(0.384)	(0.995)	(0.631)	(0.410)	(0.712)	(0.548)
L.roa	−0.277	−0.455	−0.010	0.665*	1.002	0.514
	(0.495)	(1.223)	(0.789)	(0.374)	(0.632)	(0.468)
L.level	0.140***	0.007	0.033	−0.007	−0.211**	−0.205***
	(0.040)	(0.112)	(0.067)	(0.055)	(0.097)	(0.072)
L.size	0.000	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,906	5,906	5,906	6,243	6,243	6,243
R^2	0.040	0.064	0.071	0.047	0.080	0.080

This table reports robust panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of high information disclosure quality groups and low information disclosure quality groups. The total sample is divided into two subsamples: lower and higher groups, based on 30% and 70% quartiles of KV index respectively. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 20: Robust test: regression results for different analysts coverage.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti2	0.074	0.515***	0.345***	0.029	−0.027	−0.073
	(0.076)	(0.154)	(0.107)	(0.113)	(0.267)	(0.190)
L.CRASH	−0.178***			−0.203***		
	(0.012)			(0.027)		
L.NCSKEW		−0.136***			−0.182***	
		(0.012)			(0.025)	
L.DUVOL			−0.139***			−0.192***
			(0.012)			(0.024)
L.ret	0.713	7.801***	5.910***	2.251*	6.580**	4.741**
	(0.507)	(1.019)	(0.729)	(1.342)	(3.080)	(2.039)
L.sigma	−0.351	−0.211	−0.666	−1.794***	−1.440	−1.033
	(0.265)	(0.594)	(0.421)	(0.566)	(1.363)	(0.868)
L.roa	0.569**	1.054*	0.414	0.179	0.860	0.371
	(0.277)	(0.556)	(0.380)	(0.742)	(1.585)	(1.046)
L.level	−0.010	−0.106	−0.110*	0.020	−0.181	−0.090
	(0.040)	(0.087)	(0.062)	(0.086)	(0.206)	(0.128)
L.size	0.000	0.000**	0.000***	0.000	0.000*	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,028	5,028	5,028	4,809	4,809	4,809
R^2	0.067	0.069	0.068	0.071	0.118	0.119

This table reports robust panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of low analysts' attention groups and high analysts' attention groups. We used the total number of analysts coverage of firms to measure analysts' attention. We used the 30% and 70% quartiles of analysts' attention as the cut-off, and the firms were divided into low and high attention groups. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 21: Robust test: regression results for different institutional holding group.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti2	0.102**	0.481***	0.358***	0.028	0.037	−0.027
	(0.044)	(0.176)	(0.124)	(0.106)	(0.220)	(0.144)
L.CRASH	−0.198***			−0.174***		
	(0.020)			(0.015)		
L.NCSKEW		−0.131***			−0.161***	
		(0.015)			(0.020)	
L.DUVOL			−0.170***			−0.182***
			(0.014)			(0.019)
L.ret	0.698	6.795***	5.479***	0.933	2.429	1.849
	(0.949)	(1.287)	(0.932)	(0.670)	(2.091)	(1.426)
L.sigma	−0.777*	0.043	0.806	−0.621*	0.018	0.540
	(0.423)	(0.696)	(0.503)	(0.335)	(0.970)	(0.642)
L.roa	0.464	0.860	0.321	0.277	0.723	0.699
	(0.509)	(0.655)	(0.505)	(0.362)	(1.178)	(0.737)
L.level	−0.094	−0.074	−0.085*	0.064	−0.367**	−0.156
	(0.065)	(0.068)	(0.048)	(0.048)	(0.159)	(0.104)
L.size	−0.000	0.000***	0.000***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,120	5,120	5,120	6,959	6,959	6,959
R^2	0.046	0.071	0.086	0.067	0.084	0.095

This table reports robust panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of low institutional shareholding groups and high institutional shareholding groups. We used the 30% and 70% quartiles of the institutional shareholding as the cut-off point, and the firms were divided into low and high shareholding groups. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 22: Robust test: regression results for different investor sentiment.

	Low			High		
	(1) CRASH	(2) NCSKEW	(3) DUVOL	(4) CRASH	(5) NCSKEW	(6) DUVOL
L.newSenti2	−0.039	0.022	−0.017	0.173***	0.544***	0.348**
	(0.101)	(0.216)	(0.147)	(0.063)	(0.210)	(0.137)
L.CRASH	−0.177***			−0.165***		
	(0.018)			(0.015)		
L.NCSKEW		−0.141***			−0.103***	
		(0.018)			(0.017)	
L.DUVOL			−0.132***			−0.125***
			(0.018)			(0.016)
L.ret	2.871***	6.671***	3.952***	2.329***	6.885***	4.676***
	(0.947)	(1.836)	(1.283)	(0.710)	(1.703)	(1.149)
L.sigma	−0.537	0.860	0.689	0.784**	0.694	0.072
	(0.422)	(0.901)	(0.592)	(0.359)	(0.865)	(0.590)
L.roa	0.751	1.287	0.873	0.676*	2.094**	1.581**
	(0.574)	(0.945)	(0.612)	(0.390)	(0.875)	(0.616)
L.level	0.035	−0.193*	−0.109*	0.023	−0.084	−0.078
	(0.064)	(0.101)	(0.064)	(0.051)	(0.120)	(0.082)
L.size	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects:						
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	5,213	5,213	5,213	6,258	6,258	6,258
R^2	0.047	0.077	0.085	0.051	0.082	0.085

This table reports robust panel estimates of stock crash risk on the news coverage sentiment by using the subsamples of pessimistic investor groups and optimistic investor groups. We used the 30% and 70% quartiles of the investor sentiment as the cut-off point, and the firms were divided into low and high shareholding groups. Columns (1) to (3) are low subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. Columns (4) to (6) are high subgroup, the dependent variables are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

Table 23: Robust test: regression of adding analyst and media coverage sentiment crossterms.

	(1) CRASH	(2) NCSKEW	(3) DUVOL
L.newSenti2	0.238**	0.618**	0.336*
	(0.117)	(0.269)	(0.185)
L.anaSenti	0.035***	0.061***	0.050***
	(0.011)	(0.023)	(0.016)
L.newSenti2#L.anaSenti	−0.121**	−0.424*	−0.186*
	(0.057)	(0.235)	(0.105)
L.CRASH	−0.150***		
	(0.009)		
L.NCSKEW		−0.099***	
		(0.009)	
L.DUVOL			−0.108***
			(0.009)
L.ret	0.933**	8.405***	5.992***
	(0.406)	(0.839)	(0.584)
L.sigma	0.528***	0.664***	0.953***
	(0.198)	(0.144)	(0.303)
L.roa	0.377*	1.260***	0.688**
	(0.217)	(0.453)	(0.308)
L.level	0.014	−0.146**	−0.112***
	(0.034)	(0.060)	(0.039)
L.size	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)
Fixed effects:			
Year dummy	Yes	Yes	Yes
Firm dummy	Yes	Yes	Yes
N	16,829	16,829	16,829
R^2	0.039	0.066	0.072

This table reports robust panel estimates of stock crash risk on the interaction between the news coverage sentiment and the analysis report sentiment. The dependent variables in columns (1), (2), and (3) are CRASH, NCSKEW, and DUVOL, respectively. All control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

5.3.1. Information Intermediation. Insiders have information that is not yet publicly available, which can be used to judge the value of the firm and predict future firm performance [34]. Insider sell-off behavior is positively associated with stock price crash risk [35]. The insider's choice to sell stocks sends negative signals to outside investors, thereby raising the probability of a future crash risk. Furthermore, the more overpriced a stock is, the greater the chance of a crash.

We thus divide the total sample into two subsamples, lower and higher groups, based on 30% and 70% quartiles of insiders' net stock sales, respectively. The regression results for various groups are shown in Table 8. The coefficients of the high net selling subgroups are significant, whereas those coefficients of the low net selling subgroups are insignificant. Thus, insiders sell more stocks, thereby amplifying the impact of media sentiment on the risk of a future stock price crash, confirming *H3a*.

We examine the quality of firm disclosure to determine if it would mitigate the bubble created by media and reduce the risk of a stock price crash. We followed the method of Kim and Verrecchia [43] (KV index) to measure the quality of information disclosure. The higher the KV index, the lower the quality of the information disclosure of listed firms.

We again divide the total sample into two subsamples based on the 30% and 70% quartiles of the KV index into lower and higher groups. The regression results for the different groups are presented in Table 9. The coefficients of the lower disclosure group are significant, whereas those coefficients of the higher disclosure group are insignificant. Thus, the effect of news coverage on the risk of a future stock price crash is significantly enhanced in firms with poor disclosure. Meanwhile, the effect of media sentiment was significantly weaker when the quality of firm disclosure is high. Thus, *H3b* is supported.

Next, we examine the Hypothesis H3c. Follow He et al. [35], we calculate the analysts coverage as the number of analysts forecast over the past three years. Then, we divide the total sample into two subsamples: lower coverage and higher coverage groups, according to 30% and 70% quantiles of analysts' coverage to firms. Table 10 presents the regression results.

The coefficients of the low analyst coverage groups are significant, indicating that positive media coverage in the previous year increases the future stock price crash risk of firms with lower analyst coverage. The coefficients of the high analyst coverage groups are insignificant, and the impact of news coverage on stock price crash risk is attenuated. Thus, news coverage sentiment has a stronger impact on stock price crash risk when analysts pay less attention to a firm, supporting *H3c*.

5.3.2. Investor Sentiment. In exploring the investor sentiment channel, we investigate whether an increase in number of retail investors could increase the emotional impact of the media. Table 11 shows the regression results for different groups, divided into low and high groups based on 30% and 70% quartiles of institutional holding.

The coefficients for the low institutional holding subgroups are significant, whereas those coefficients for the high institutional holding subgroups are insignificant. The findings suggest that as retail investors increase their holdings, they tend to behave more irrationally, thereby amplifying the emotional tendency of media sentiment. Our results support *H4a*.

We consider direct proxy variables for investor sentiment and construct investor sentiment indicators according to Rhodes-Kropf et al. [44], dividing the total sample into pessimistic and optimistic groups based on 30% and 70% quartiles of investor sentiment. The regression results for different groups are shown in Table 12. The coefficients for the pessimistic subgroups are insignificant, whereas those coefficients for the optimistic subgroups are significant. The findings suggest that optimistic investor sentiment, which increases the likelihood that the current stock price is overvalued, increases the impact of news coverage on future crash risk, supporting *H4b*.

To investigate whether disagreement between professional analysts and retail investors also enhances the risk of a stock price crash, we add the cross-term of analysts' sentiment and media sentiment into the regression (Table 13).

The proxy variable used in this study to represent consistency and disagreement is the crossterm of analysts and news sentiment. When there are significant differences between the two opinions, often one is less than 0 and the other is greater than 0, so the cross-term is negative and represents the differences in opinions. Conversely, the two types of views have the same symbol and positive multiplication, implying that they are consistent.

The results of the regression are reported in Table 13. The results demonstrate the impact of analyst-rated sentiment on future stock price crash risk. The coefficient of the cross-term is negative, consistent with our theoretical hypothesis that the future stock price crash risk decreases when media sentiment and analyst sentiments are consistent, and increases otherwise. The regression results show that divergence of opinions in the market could increase media sentiment tendencies, thereby supporting *H4c*.

5.4. Robust Test. *newSentinewSenti2* To test the robustness of the indicators, we replace the main explanatory variable of the previous regression (*newSenti*), which is the weighted average of news sentiment, with an equally weighted average (*newSenti*2) and repeat the previous regressions. The results are shown in Tables 14––23 and are consistent with those in the previous contents.

This table reports robust regression estimates of quarterly stock crash risk on the news coverage positive and negative sentiment indicators. Columns (1) to (4) are positive indicators. Columns (5) to (8) are negative indicators; quarter and firm dummy variable are included; all control variables are included as lagged one year. Robust standard errors are reported in parentheses. The labels $***$, $**$, and $*$ indicate 1%, 5%, and 10% levels of significance, respectively.

6. Conclusions

We construct a deep learning model of stock news sentiment recognition based on the advanced approach of financial knowledge dictionary and NLP (BERT-based pretraining) technology. We use this model to calculate the sentiment indicators of all stocks from 2011 to 2020. Subsequently, we analyze the impact of media sentiment on future stock price crash risk and its heterogeneity.

We find that average media sentiment exacerbates the risk of future stock price crashes. The heterogeneity results indicate that positive coverage significantly increases future stock price crash risk, whereas negative coverage has a limited effect. However, negative coverage is highly correlated with current stock price crash risk. We also investigate the information intermediation and investor sentiment channels by which media sentiment affects the risk of a crash. The results show that more net insider sales, lower information transparency, and less analyst coverage amplify the impact of media sentiment on future crash risk, which is consistent with the information intermediation channel. Additionally, more retail investor positions, more active investor sentiment, and divergence between analysts' opinions and news amplify the impact of news sentiment on the risk of a future stock price crash, which is consistent with the investor sentiment channel.

Our finding that positive media sentiment can lead to an extreme outcome in the stock market is useful for both regulators and investors. Our examination of the impact of media sentiment on the future stock price crash risk adopted both behavioral finance and information economics perspectives, and revealed that investors' irrational and excessive optimism could be a major cause of stock price bubbles and crashes in China's stock market, which is dominated by retail investors who are restricted from short selling.

In terms of research methodology, our study combined advanced deep learning and dictionary methods, fully utilizing computer performance and intelligence to significantly improve the recognition accuracy and efficiency of massive amounts of sentiment data. To the best of our knowledge, we are the first to combine deep learning and dictionary methods for sentiment analysis in finance, thereby broadening the scope of sentiment analysis methods in finance.

Data Availability

The data copyright belongs to the GuoTai'an and Wind, disclosing is not allowed.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Causality Tests and Their Applications to China's Stock and Housing Markets

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The link between the stock market and the housing market is well known to be sensitive. At present, the possibility of a connection between them remains intriguing. Therefore, China works as a case study for the research inquiry into the causal relationship between the stock market and the housing market. Using the monthly data from January 2000 to January 2021 and employing the cross-correlation function approach to perform empirical analysis, the results indicate that the bidirectional causal relationship between the stock market and the housing market has been recognized as one of the most interesting findings, which constitutes a significant departure from previous research. Moreover, the other interesting result is that, from the housing market to the stock market, a causality-in-mean and a causality-in-variance are discovered. Only a tiny number of previous studies have addressed this achievement in the context of China. Meanwhile, this article's findings have both theoretical and practical implications for China's proposition.

1. Introduction

It is common knowledge that China's stock market and housing market are two of its most important markets. Their unpredictable pricing has a significant impact on China's economic growth. As a result of this background, a significant number of academic researchers have focused their attention on investigating the connection between the housing market and the stock market. Despite this, academics have not yet arrived at a decision about the connection between the two of them due to their different samples and approaches. Using the autoregressive distributed lag cointegration technique, Gounopoulos et al. [1] claimed that there was a positive association between the volatilities of the stock market and the housing market. Meanwhile, Abuzayed et al. [2] came up much later and confirmed this viewpoint as well. However, employing the quasi-maximum-likelihood approach to estimate unknown parameters of the cDCC-GJR-GARCH model, a number of academics, such as Lou [3] and Deng et al. [4], were of the opinion that the volatilities of the stock market and the housing market did not have a positive link with one another. The fact that the conclusion of divergence might vary by such a large amount completely demonstrated that the rule of correlation between the volatilities of two markets had not been consistently identified.

When taking into consideration the current state of China's economy, the Chinese government places a high premium on the fact that the stock market experiences significant swings and that housing prices continue to climb. In response, a wide range of regulatory interventions have been implemented in an effort to combat this issue. For example, the government has put limits on who can buy houses and how they can pay for them. This is an attempt to lower the level of demand in the housing market. In the meantime, the government has also made improvements to the system that is designed to prohibit and regulate speculative trading on the stock market to lower the level of risk associated with trading on the stock market, but the problem of housing prices that are too high has not been properly addressed or solved. In addition to this, the stock market is subject to wild swings in volatility on occasion. Even more alarming is the fact that the consequences of the policy are far less than we expected. China's degree of financial

development is considered to be at the lower end of the spectrum when compared to that of developed countries. Investors have a limited number of options when it comes to markets and items that provide large earnings. As a result, the majority of investors opt to put their money into either the stock market or the housing market. To phrase this another way, it is worthwhile to conduct an investigation into the connection that exists between the stock market and the housing market. To be more explicit, on the one hand, it is beneficial for investors to forecast the trajectory of economic development and to rationally organize their asset portfolio in accordance with the data that correspond to this trajectory. On the other hand, it gives the Chinese government a clear point of reference for figuring out what the rule means based on the state of the economy at the time. In fact, analyzing both the housing market and the stock market is important for controlling financial risks and preventing too many market bubbles from forming. Both the healthy growth and consistent growth of the stock market and the housing market are supported by the importance of both of these factors.

In line with the findings of Hafner and Herwartz [5], the cross-correlation function approach is employed to analyze the causal link between China's housing market and the stock market. In fact, several researchers, such as Alaganar and Bhar [6], Nakajima and Hamori [7], and Toyoshima and Hamori [8], have employed the cross-correlation function approach to undertake studies on the commodities market, the stock market, and the business cycle. Meanwhile, with regard to the study that Hafner and Herwartz [9] have conducted, the Granger causality test is used to examine the causality-in-mean. In addition, in reference to the work of Chang and McAleer [10], the causality-in-mean or the causality-in-variance is examined using the cross-correlation function approach. In comparison with the work of Hong [11], the cross-correlation function approach has the significant advantage of being easy to not only investigate the causality direction but also validate the appropriate lag length and lead length. This is the most obvious advantage of the cross-correlation function approach. Moreover, the cross-correlation function technique enables both flexible specification of the innovation process and independence from normality, as can be shown by examining the work of Dakhlaoui and Aloui [12]. In view of the discoveries presented above, this study uses the monthly data from January 2000 to January 2021 and employs the cross-correlation function approach to investigate the connection between China's stock market and the housing market. The empirical results bring about two important findings. First, it is found that there is a two-way causal relationship between China's stock market and the housing market. Second, from the housing market to the stock market, we found a causality-in-mean and a causality-in-variance.

In three different ways, this study makes a contribution to the existing body of research on the topic of the connection between China's stock market and the housing market. First, in 2021, the World Federation of Exchanges reported that the value of the real estate market in China, which was now estimated to be $ 62 trillion US dollars, was the greatest asset in the world. Meanwhile, based on the Wind Database, when compared to the average size of 5 trillion yuan in 2001, the entire market value of A shares was around 80 trillion yuan by the end of December 2020. This represented a growth of almost 15 times compared with size of the market in 2001. The number of listed firms surpassed 4,100, which was almost four times as much as in 2001. To sum up, it is more representative to take China as a sample to investigate the relationship between China's stock market and the housing market, compared with Jang et al. [13], who studied this issue with the sample of Korea, and Sing et al. [14], who studied this topic with the sample of Singapore. Second, the cross-correlation function approach used in this study to conduct empirical analysis might produce more reliable findings, compared with Li et al. [15] and Bahmani-Oskooee and Wu [16], who used the bootstrap Granger causality test, and Yousaf and Ali [17], who used the vector error correction method. Third, one of the most intriguing discoveries, which represents a substantial divergence from past research, is the bidirectional causal link between the stock market and the housing market. Another intriguing finding is the discovery of a causality-in-mean and a causality-in-variance from the housing market to the stock market. Only a few previous studies have examined this accomplishment in the contest of China.

The remainder of this work is delivered in the following order, according to its organizational structure. The literature review is presented in Section 2. The approach known as the cross-correlation function is shown in Section 3. The results and discussions are provided in Section 4. The conclusion is reported in Section 5.

2. Literature Review

Despite the vast amounts of research that have been conducted on the subject of the connection between the stock market and the housing market, many researchers have not been able to arrive at a consensus about this proposition. The reason for this is that various pieces of research could use various econometric methodologies, samples, and time periods to come to their conclusions.

According to Hartzell et al. [18], the features of common stock may be seen as a hedge against inflation. They came to the conclusion that the actual return on equity had a negative impact, regardless of whether it was anticipated or unanticipated inflation. Gyourko and Keim [19] explored the link between the returns of real estate stock and the returns of a typical appraisal-based index in the context of the American real estate markets. When the consistency in appraisal series was taken into account, they found that the returns of real estate portfolio lags could predict the returns of an appraisal-based index. However, Quan and Titman [20] investigated the association between shifts in property prices and rents and stock returns using data spanning fourteen years and fourteen countries throughout a total of fourteen years. They looked at the data and came to the conclusion that there was no statistically significant connection between fluctuations in annual real estate prices and returns on stock investments. In contrast to the study conducted by Gyourko and Keim

[19], Okunev et al. [21] investigated the connection between the S&P 500 stock markets and real estate in the United States using year-to-year time-series data spanning the period from 1972 to 1998. They carried out empirical studies using both the linear causality test and the nonlinear causality test, and the results showed that there was a link running only one way, from the real estate market to the stock market. However, the financial hypothesis was disproved by this discovery. On the contrary, the findings of the nonlinear causality test indicated that there was a robust one-way link running from the stock market to the real estate market. This conclusion was reached as a direct consequence of the findings. Furthermore, this finding confirmed the presence of structural breaks. Moreover, these outcomes were supported by Tzeremes [22], Hui and Yu [23], and Sing [24].

In the context of Greece, Kapopoulos and Siokis [25] investigated the connection between fluctuations in the value of real estate and the stock market. They supplied two different interpretations of this interaction between the two of them. There were a wealth effect and a credit price effect. The former suggested that when there was a rise in share price, the household earned unforeseen benefits, and there was a tendency for the quantity of housing to grow. The latter suggested that a rise in real estate prices was beneficial to economic activity and the future profitability of businesses. They used the Granger causality to provide an all-encompassing understanding of both systems. They came to the conclusion that the wealth effect hypothesis could only be substantiated for the real estate values in Athens. However, the wealth effect hypothesis about the pricing of other urban real estates could not be supported. In addition, Liow and Yang [26] used the vector error correction model and the fractional integrated vector error correction model to investigate whether or not the stock market and the securitized real estate market shared long-run co-memories. They found a fractional cointegration between the price of stocks on the market, the price of securitized real estate, and certain important factors affecting the macroeconomy. Given the predominance of fractional cointegration, this indicated that securitized real estate and common stock were, in the long term, alternative assets that might not be placed together in a diverse manner. Similarly, Liow [27] investigated the long-run and short-run links between the property and stock markets. He identified a long-term contemporaneous link between property prices and stock prices using autoregressive distributed lag cointegration. Furthermore, when adjusting for changes in macroeconomic impact, the long-run and short-run effects of residential and office building comprehensive pricing on the stock market were diminished. While the price of office property had the greatest long-run influence on the stock market, the impact of residential property prices on the stock market was greater in the short run. Meanwhile, Chiang and Chen [28] and Liang et al. [29] agreed with the above findings.

In the case of China, Liu and Su [30] examined the link between the real estate market and the stock market using the asymmetrical threshold cointegration test. In the long term, they discovered a nonlinear correlation between the Shenzhen Composite Index and the Real Estate Price Index. He discovered that there was a unidirectional causality flowing from stock price to house price using the vector autoregressive framework for empirical analysis. Su [31] used the nonparametric rank test on a sample of Western European countries to confirm the nonlinear equilibrium link between the real estate market and the stock market. Using the threshold error correction model, he found that, in the long run, the real estate market and the stock market were linked in a way that only ran in one direction. Similarly, Su et al. [32] used both the threshold error correction model and the threshold autoregressive model to look into the same topic. Even though the methods of analysis were distinct, they both ended up with the same conclusion. In addition, Su et al. [33] used a case study of China to reexamine this subject by including more factors in their analysis. In the long run, they discovered that changes in the price of real estate might have an effect on the price of shocks. Yousaf and Ali [17] looked at the relationship between real estate and the stock market in Pakistan using the vector error correction model. They discovered that there was a cointegration relationship between the real estate market and the stock market. In a more concrete sense, the long-run causal link between housing markets and stock markets was seen to run from one to the other. Furthermore, the above results were consistent with Nong [34], and Zou and Deng [35].

In contrast to the previous studies, the objective of this investigation is to determine whether or not there is a connection between the stock market and the housing market using the causality-in-mean test and the causality-in-variance test in the case study of China. As a result of this investigation, it has been found that there is a two-way link between the stock market and the housing market. This is a new development based on previously conducted research. The findings of the tests of causality-in-mean and causality-in-mean have shown that the casual link runs from the housing market to the stock market. These tests study whether or not the housing market has an effect on the stock market. This finding has never been highlighted in any of the previous investigations.

3. Methodology

Caporale et al. [36] and Whang and Kim [37] say to assume that there are two time series, H and S, that are stationary. Meanwhile, they define the information sets as $A_{1,t}$, $A_{2,t}$, and $A_{3,t}$. The forms of these three information sets are shown as follows:

$$\begin{aligned} A_{1,t} &= (H_t, H_{t-1}, H_{t-2}, H_{t-3}, \ldots), \\ A_{2,t} &= (S_t, S_{t-1}, S_{t-2}, S_{t-3}, \ldots), \\ A_{3,t} &= (H_t, H_{t-1}, H_{t-2}, H_{t-3}, \ldots, S_t, S_{t-1}, S_{t-2}, S_{t-3}, \ldots). \end{aligned} \tag{1}$$

If $E(H_t|A_{1,t-1}) \neq E(H_t|A_{t-1})$, S is stated to be the cause of H in the mean. Likewise, if $E(S_t|A_{2,t-1}) \neq E(S_t|A_{t-1})$, H is stated to be the cause of S in the mean. Moreover, if $E(H_t|A_{1,t-1}) \neq E(H_t|A_{t-1})$ and $E(S_t|A_{2,t-1}) \neq E(S_t|A_{t-1})$ hold simultaneously, there will be a feedback effect between

H and S in the mean. However, if $E((H_t - m_{H,t})^2|A_{1,t-1}) \neq E((H_t - m_{H,t})^2|A_{t-1})$, S is stated to be the cause of H in the variance. Likewise, if $E((S_t - m_{S,t})^2|A_{2,t-1}) \neq E((S_t - m_{S,t})^2|A_{t-1})$, H is stated to be the cause of S in the variance. There into, $m_{H,t}$ is the mean of H under the condition of $A_{1,t-1}$. $\mu_{m,t}$ is the mean of S_t under the condition of $A_{2,t-1}$. Similarly, if $E((H_t - m_{H,t})^2|A_{1,t-1}) \neq E((H_t - m_{H,t})^2|A_{t-1})$ and $E((S_t - m_{S,t})^2|A_{2,t-1}) \neq E((S_t - m_{S,t})^2|A_{t-1})$ hold at the same time, there will be a feedback effect between H and S in the variance. Taking these four inequalities into consideration, the causality-in-mean and causality-in-variance can be examined. Then, H_t and S_t can be defined as follows:

$$\begin{aligned} H_t &= m_{H,t} + (w_H \varepsilon_t)^{1/2}, \\ S_t &= m_{s,t} + (w_s \mu_t)^{1/2}, \end{aligned} \tag{2}$$

where ε_t and μ_t denote the white noise and independence. The standardized innovation for the causality-in-mean test is as follows:

$$\begin{aligned} \zeta_t &= \frac{(H_t - m_{H,t})^2}{w_H} = \varepsilon_t^2, \\ \xi_t &= \frac{(S_t - m_{S,t})^2}{w_S} = \mu_t^2, \end{aligned} \tag{3}$$

where ζ_t and ξ_t denote the standardized residuals. We use estimates for these residuals because they are unobservable. The sample cross-correlation of the squared standardized residual series, $r_{\zeta\xi}(k)$, is then calculated using their estimations. The sample cross-correlation is computed utilizing the standardized residual series, $r_{\varepsilon\mu}(k)$, with lag k.

Using the cross-correlation function method, the number of $r_{\zeta\xi}(k)$ and $r_{\varepsilon\mu}(k)$ is employed to identify causality-in-mean and causality-in-variance, correspondingly. Then, the following cross-correlation function statistic allows to identify the null hypothesis that there is no causality-in-mean.

$$T_{CCF} = T^{1/2} r_{\varepsilon\mu}(k). \tag{4}$$

The null hypothesis cannot be rejected if the cross-correlation function test statistic, T_{CCF}, falls under the critical value obtained by employing the standard normal distribution. Similarly, using the following test statistic, the null hypothesis that causality-in-variance does not exist may be identified.

$$T_{CCF} = T^{1/2} r_{\zeta\xi}(k). \tag{5}$$

The null hypothesis cannot be rejected if the cross-correlation function test statistic, T_{CCF}, falls under the critical value obtained by employing the standard normal distribution. The test of the cross-correlation function technique consists of two parts. One is that the univariate time-series models, which take into account the conditional means and variances that vary throughout time, are estimated. Following Engle and Bollerslev [38], and Hwang and Valls Pereira [39], the AR-EGARCH formulation is used in this study. The other is that we compute the standardized residuals of the estimated AR-EGARCH model and then the standardized squared residuals' series via conditional variances from the estimated model. As previously stated, the cross-correlation function of these standardized residuals is used to confirm the null hypothesis that there are no causality-in-mean and causality-in-variance.

4. Results and Discussion

4.1. Basic Statistic Description. Using monthly time-series data regarding China's stock and housing markets from January 2000 to January 2021, this study investigates the link between the stock market and housing market by employing casualty-in-mean and casualty-in-variance tests. The housing price index and the CSI300 index are obtained from Investing.com. The basic characteristics of the housing price index and the CSI300 index are presented in Table 1.

Following Jarque and Bera [40], the Jarque–Bera statistics are used to determine whether the change rates of both the housing market and the shock market have a normal distribution. According to the findings of Table 1, the normality of both the housing market and the shock market is rejected at a 5% significant level due to the value of probability. It is known that stationary variables serve as the foundation for the AR-EGARCH model and the causality test. Following Damianov and Elsayed [41] and Lee et al. [42], unit root tests such as KwiatKowski–Phillips–Schmidt–Shin (KPSS) test and Zivot and Andrews (ZA) test are employed in this study. The results of KPSS test indicate that the null hypothesis is not rejected. It means that the variables investigated are stationary. Moreover, the results of ZA test indicate that the null hypothesis is rejected at a 1% significant level, as shown in Table 1. In other words, the variables highlighted in this study are stationary.

4.2. AR-EGARCH Model. The cross-correlation function technique is used to assess the link between change rates in stock and housing prices. The AR(k)-EGARCH (p, q) model is shown as follows:

$$x_t = a_0 + \sum_{i=1}^{k} a_i x_t + b_0 du\ m_t + \omega_t, \tag{6}$$

$$\log(\sigma_t^2) = \nu + \sum_{i=1}^{q} (a_i|z_{t-i} + \delta_i z_{t-i}) + \sum_{i=1}^{p} \beta_i \log(\sigma_{t-1}^2), \tag{7}$$

where ω_t denotes the white noise; $du\ m_t$ denotes the dummy variable (before January 2008, the value is zero; otherwise, the value is one); z_t denotes the ω_t/σ_t; and $\log(\sigma_t^2)$ denotes the conditional variance in log. Following Jane and Ding [43], Martinet and McAleer [44], and Chang and McAleer [45], employing the log version of the EGARCH (p, q) model, it is feasible to ensure non-negativeness without applying coefficient restrictions. The EGARCH (p, q) model represents the asymmetric impact of negative and positive shocks by incorporating the term z_{t-i}. When δ_i is greater than zero, $z_{t-1} = \omega_{t-1}/\sigma_{t-1}$ is positive. $\sum_{i=1}^{p} \beta_i$ describes the

Table 1: Results of basic statistic description.

Statistics and variable	HPI	CSI300
Mean	0.049	0.005
Median	0.052	0.003
Maximum	0.126	0.258
Minimum	−0.061	−0.210
Standard error	0.048	0.068
Skewness	−0.541	0.383
Kurtosis	2.500	5.041
Jarque–Bera	6.460	21.584
Probability	0.040	0.000
Observations	109	109
KPSS test	0.715	0.491
ZA test	12.943***	6.012***

Note. HPI represents the change rate of the house price index; CSI300 represents the change rate of the stock index; and ***represents a 1% significant level; null hypothesis of KPSS test is that the variable is stationary; null hypothesis of ZA test is that the variable has a unit root.

Table 2: Results of the AR-EGARCH model.

Model	AR (3)-EGARCH (1, 1)	AR (1)-EGARCH (1, 1)
Coefficient and variable	HPI	CSI300
a_0	0.049***(0.002)	−0.020*** (0.000)
a_1	1.108*** (0.269)	0.981*** (0.000)
a_2	0.476*** (0.008)	
a_3	−0.629** (0.012)	
b_0	−0.001 (0.004)	0.015** (0.042)
ν	−0.724** (0.019)	−0.894*** (0.006)
a_1	0.746*** (0.008)	0.758*** (0.000)
γ_1	−0.028 (0.864)	−0.120*** (0.001)
β_1	0.429* (0.099)	0.471* (0.053)
Log likelihood	468.642	390.649
SBIC	−8.358	−6.931
$Q(20)$	21.620 (0.523)	24.143 (0.453)
$Q^2(20)$	41.205 (0.214)	40.832 (0.266)

Note. * represents a 10% significant level; ** represents a 5% significant level; *** represents a 1% significant level; Q represents the Ljung–Box statistics; () represents the p value.

persistence of shocks to the conditional variance. Equation (6), which represents the conditional mean, is expressed as a k-order autoregressive model. Following Schwarz [46], the Schwartz–Bayesian information criterion is used to calculate the optimal lag length, k, for each variable. In equation (7), the Schwartz–Bayesian information criterion is also used to find out the optimal lag lengths p and q. The model utilized in this study is from EGARCH (p, q), in which $p \in [1, 2]$ and $q \in [1, 2]$. Table 2 displays the results of the AR(k)-EGARCH (p, q) model.

The value of β_1, which is shown in Table 2, is used to figure out how persistent the volatility is. It is found that β_1 is significant at a 10% level. This indicates that the persistence of volatility shocks occurs. A possible explanation of this outcome is that the stock market and housing market in China are both experiencing a period of fast expansion. The volatile performance of listed companies, the severe imbalance between supply and demand in the stock market, the imperfect market operation mechanism, the aggravation of stock market fluctuations caused by stock market policies, and the excessive manipulation of market makers are some of the factors that may lead to the continued occurrence of volatility shocks. Moreover, this study's findings may offer policymakers a foundation for formulating policies to lessen the volatility of the stock market and housing market. The findings of this study may potentially serve as a foundation for future research on the subject, particularly if it is conducted in conjunction with other economic information or methodologies. The findings of this article also provide potential investors with a foundation on which to base their decisions. It is possible for investors to maximize their profit chances while also reducing their investment risks if they have a thorough grasp of the persistent influence that volatility has on China's stock market and housing market. Meanwhile, the results of this study provide a basis for the public to participate in the stock market and purchase real estate because an in-depth understanding of the causes of the persistent volatility of China's stock market and real estate market and the linkage between them can assist the public in reducing the risk associated with participating in the stock market and purchasing real estate. In the meantime, the diagnostic test results for the AR (3)-EGARCH (1, 1) and AR (1)-EGARCH (1, 1) are reported in Table 2. According to Ljung and Box [47], the autocorrelation is diagnosed using the Ljung–Box statistic. Based on the results of $Q(20)$ and $Q^2(20)$, the null hypothesis of no autocorrelation is not rejected. In other words, no autocorrelation is detected up to 20th order. To conclude, these findings provide empirical evidence in favor of the AR-EGARCH model that is formulated. Then, we use the estimated sample cross-correlations to conduct an investigation of the causality-in-mean and causality-in-variance. The results are shown in Table 3.

When the HPI and CSI300 ($-k$) are taken into consideration, the result suggests that in lag 5, the causality-in-mean emerges at a 10% significant level. Meanwhile, the results show that the causality-in-variance appears at a 5% and 10% significant level in lags 3 and 8, respectively. In addition, the results of the HPI and CSI300 ($+k$) sample show that the causality-in-mean appears at a 5% significant level in lag 15. Simultaneously, the result also indicates that both at lag 5 and at lag 13, the causality-in-variance occurs at a 10% significant level. In a nutshell, this study presents an overview of two interesting discoveries. One is that, in spite of the fact that Ding et al. [48] discovered a unidirectional causality extending from China's housing market to the stock market, this research demonstrates that bidirectional causality exists between the housing market and the stock market. This provided evidence for the existence of both a credit price effect and a wealth effect between stock market and the housing market. The other is that there is evidence of a causal link between stock and housing markets, in terms of both causality-in-mean and casualty-in-variance. In fact, only a few of the previous studies that have been done on China have highlighted this achievement. Moreover, either researchers working in the field or those working in academic institutions may gain something from the results reported in this work.

Table 3: Results of cross-correlation test.

Lag (k)	HPI and CSI300 ($-k$)		HPI and CSI300 ($+k$)	
	Mean	Variance	Mean	Variance
1	−0.052	−0.009	−0.130	−0.127
2	−0.042	−0.146	0.041	−0.052
3	−0.054	0.116**	−0.109	−0.087
4	0.022	−0.234	−0.073	−0.020
5	0.099*	−0.039	−0.101	0.033*
6	−0.123	−0.099	0.134	−0.029
7	0.047	−0.070	−0.090	−0.104
8	−0.064	0.184*	−0.150	0.128
9	0.043	0.022	−0.135	−0.073
10	0.042	0.038	−0.012	−0.082
11	0.216	0.006	0.159	0.064
12	−0.069	0.021	−0.107	−0.029
13	−0.049	0.033	−0.017	0.040*
14	−0.131	−0.122	0.129	−0.093
15	−0.104	0.118	0.177**	0.019
16	0.118	−0.206	−0.066	0.046
17	0.153	−0.179	0.043	−0.006
18	0.014	−0.012	−0.046	0.088
19	−0.101	−0.054	0.023	−0.085
20	0.180	0.218	0.177	0.111

Note. * represents a 10% significant level; ** represents a 5% significant level.

Table 4: Results of cross-correlation test.

Lag (k)	HPI and SSE50 ($-k$)		HPI and SSE50 ($+k$)	
	Mean	Variance	Mean	Variance
1	−0.059	−0.008	−0.116	−0.121
2	−0.074	−0.166	0.087	−0.064
3	−0.097	0.144*	−0.128	−0.028
4	0.08	−0.248	−0.040	−0.031
5	0.082***	−0.039	−0.103	0.087**
6	−0.151	−0.085	0.139	−0.030
7	0.02	−0.050	−0.087	−0.148
8	−0.073	0.145**	−0.198	0.142
9	0.012*	0.057	−0.114	−0.031
10	0.049	0.036	−0.083	−0.084
11	0.225	0.003	0.146	0.053
12	−0.062	0.24	−0.165	−0.075
13	−0.022	0.039	−0.027	0.036***
14	−0.072	−0.184	0.156	−0.086
15	−0.127	0.161	0.171*	0.026
16	0.184	−0.269	−0.097	0.083
17	0.125	−0.071	0.029	−0.034
18	0.056	−0.093	−0.074	0.080
19	−0.134	−0.012	0.030	−0.046
20	0.123	0.138	0.172	0.116

Note. * represents a 10% significant level; ** represents a 5% significant level; *** represents a 1% significant level.

4.3. Robustness Test. This subsection provides an explanation of a robust test that may be used to validate the findings of empirical research. Following Tsai [49], Shi et al. [50], and Mori [51], for the purpose of providing an explanation for the rationale behind utilizing CSI300 index as the proxy variable for stock market performance, the SSE50 index, which is another major Chinese stock index, is included in the process of assessing the relationship between the shock market and the housing market. Using the same method, the relationship between the stock market (SSE50 index) and the housing market is reestimated. The results are shown in Table 4.

As the results of Table 4 indicate, for HPI and SSE50 ($-k$), the causality-in-mean is found in lag 5 and lag 9. Meanwhile, the causality-in-variance is found in lag 3 and lag 8. For HPI and SSE50 ($+k$), the causality-in-mean is found in lag 15. In the meantime, the causality-in-variance is found in lag 5 and lag 13. Moreover, the above findings are consistent with the results reported in Table 2. Consequently, it can be concluded that the results presented in this study are reliable and robust.

5. Conclusions

The objective of this study is to determine whether or not there is a causal relationship between the stock market and the housing market in China by analyzing the monthly data from January 2000 to January 2021. Using the cross-correlation approach for empirical analysis, two fascinating results have been obtained. One discovery is the identification of a two-way causal relationship between the stock market and the housing market. In contrast to previous studies, such as the one conducted by Zhou et al. [52], who discovered that there was a unidirectional link of causality between the stock market and the housing market, the current finding is different from the previous ones. As a direct result of this, it is possible to identify not just the credit price effect but also the wealth effect that exists between the stock market and the housing market. The other discovery is that the causality-in-mean and the causality-in-variance between the stock market and the housing market are detected. In point of fact, only a very small percentage of the previous studies that were conducted on China recognized this accomplishment.

In addition, some policy implications are suggested in light of the results and conclusions of this article. First, our findings are straightforward enough to reassure financial institutions and investors that failing to account for the presence of a time-scale dimension in stock and housing relationships, particularly during the economic crisis in 2008 and the COVID-19 pandemic in 2020, will almost certainly lead to an inaccurate assertion of portfolio measuring performance and diversification benefits. Second, the bubble that has developed in China's housing market is becoming an increasingly severe problem, which has posed a significant risk to China's overall economic growth. As a result of the connection between China's shock market and the housing market, the Chinese government is able to manage and relieve the froth in China's housing market by regulating the corresponding stock markets.

This study contributes to the current body of knowledge on the relationship between China's stock market and housing market in three distinct ways. First, since China has the greatest housing market and the fastest-growing stock market, China is a more representative sample to study the relationship between the stock market and the housing

market. Second, compared with the bootstrap Granger causality test and the vector error correction technique, the cross-correlation function approach utilized in this study to undertake empirical analysis may yield more accurate results. Third, the bidirectional causal relationship between the stock market and the housing market is one of the most exciting conclusions, which constitutes a significant departure from prior studies. The observation of a causality-in-mean and a causality-in-variance from the housing market to the stock market is another noteworthy conclusion. Only a few prior studies have studied this achievement in China.

In conclusion, this article has several limitations, some of which might open up new avenues of investigation for specialists in the relevant fields. First, this study does not take into account other macroeconomic variables, such as consumer price index and interest rate, so it does not cover such topics. It is possible for future researchers to reexamine this subject in conjunction with these macroeconomic variables, which may lead to findings that are both more effective and more intriguing. Second, due to the limitations of the cross-correlation function approach, future researchers may attempt some additional methods, such as threshold cointegration approach and vector autoregressive approach, which may result in some interesting results than the method that was used in this study. Third, to investigate the subject at hand, this study exclusively focuses on China as its case study. In the future, academics may examine this issue using the United States, Japan, Britain, and other countries as examples, which may result in some alternative findings being drawn. Four cyclical fluctuations, such as booms and busts, will have an impact on the stock and housing markets. It is possible for future researchers to take this into account in their empirical investigation, which may lead to results that are both more trustworthy and interesting.

Data Availability

The data used in this study can be available upon reasonable request from the author.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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Research Article

Vulnerability of Sustainable Islamic Stock Returns to Implied Market Volatilities: An Asymmetric Approach

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There has been increasing interests in the sustainable way of investing as enjoined by several sustainability initiatives. However, investors require effective portfolio diversification at various market conditions (stress, benign, and boom) and would consider sustainable equities to the extent that they aid in the minimisation of portfolio risks. As a result, a better way investors can mitigate portfolio risk is by forming portfolios with relevant volatility indices as enshrined in extant literature. It becomes necessary to investigate the susceptibility of Islamic stocks in a sustainable way to shocks from volatility indices to enhance effective portfolio decisions. In this regard, we investigate the asymmetric effect of implied volatility indices on sustainable Islamic stocks across different market conditions. Hence, the quantile regression and quantile-on-quantile regression techniques are employed. The study discovered an asymmetric influence of volatility on sustainable Islamic stock returns at various quantiles. Furthermore, most volatilities' asymmetric effects were generally inversely associated to sustainable Islamic stock returns, implying diversification benefits across market outcomes. Also, with the exception of the extreme quantiles, there is a causal effect of volatilities on Islamic stock returns for most quantiles. It seems to reason that ordinary market outcomes, rather than market stress or boom, have a greater impact on causal estimates for our quantile regression model.

1. Introduction

The popularity of Islamic stocks has heightened over the years to induce the attention of investors, policymakers, researchers, asset managers, etc. This is as a result of their increased market performance relative to the conventional way of investing, even in times of crises. Investing in Islamic stocks further grants the opportunity to channel ones religious belief [1, 2]. Aside from this, the high levels of integration among most conventional assets (see [3–5]) requires that effective portfolios are formed with Islamic stocks due to the latter's high extent of satisfying investors' risk tolerance in times of crises [2, 6].

However, prior studies utilising Islamic stocks alone divulge that Islamic stocks exhibit similar patterns of high interactions [7, 8] depicting low degrees of diversification in the future. This is not surprising because, although Islamic stocks are mostly insulated from existing crises, their similar response to shocks weaken diversification potentials at various investment horizons.

This has brought about many empirical studies to investigate diversification benefits among conventional and Islamic assets simultaneously [2, 6, 9–12]. Findings from these studies generally divulge some considerable levels of interactions or contagion (increased in correlations after the onset of crises) among conventional and Islamic equities.

Comparatively, conventional equities are found to exhibit more volatility spillovers of excessive interactions than their Islamic counterparts [2] during market stress. Insights from these studies are that it is better to diversify among conventional as well as Islamic equities rather than concentrating on a particular asset class.

This opens up a gap to further assess the asymmetric effect of implied market volatilities which are forward-looking. Application of implied volatilities has gained massive attention with conventional stocks [13, 14] and cryptocurrencies [15–17], as well as commodities [5, 18, 19]. It is normally found from these studies that negative shocks are mostly transmitted from the implied market volatilities to these assets demonstrating diversification, hedge, or safe haven benefits depending on the market conditions as a result of portfolio formation.

It becomes pertinent to examine the asymmetric effect of implied volatilities on Islamic stocks which have gained investors' attention over time [20–22]. This is particularly important because Islamic stocks are most likely than not susceptible to external shocks [22, 23]. This empirical discourse would highlight the relevance of forming reliable portfolios among market volatility indices as external shocks transmitters and Islamic stocks. It would also give a chance to the existing investors of Islamic stocks to reconstruct or rebalance their portfolios to incorporate implied market volatilities. Also, observing the asymmetric effect of implied market volatilities provides existing investors of Islamic stocks the opportunity to hedge against shock transmission regarding contagion effect to either redeploy or scale up their investments.

Hence, a nascent and fledgling body of literature investigates the nexus between implied volatilities and Islamic stock returns. For instance, Karim and Masih [20] through the wavelet approach investigated the asymmetric impact of realised and implied crude oil volatility on Islamic stock returns. However, the study of Karim and Masih [20] was limited to the oil market, thereby creating a myopic view of the nexus. The closest study to ours is that of Chang et al. [1], but did not consider the influence of implied volatilities in the nexus.

Some of the implied volatilities that have spillover effects on most financial markets around the world include the US VIX as a significant measure of investor fear and expectations [14], implied volatility in the energy markets, emerging markets volatility, and developed markets volatility. These implied volatilities have been touted to have ravaging impact on financial markets [5, 13, 16, 18, 24] from which Islamic stocks could be more sensitive as a result of contagion effect from markets interactions.

This is because, recently, Islamic stocks are becoming linked to shocks from implied volatilities [22, 24]. This can be traced from the behaviour of conventional investors and fund managers who seek to invest in Islamic stocks to minimise losses during crises. In times of crises, firms with a relatively huge indebtedness tend to receive most of the shocks, wherein, Sharia-compliant firms operate around a certain interest-bearing debt threshold of about 33% in accordance with the screening method of Dow Jones Sharia, to mention a few. This filtering criterion mitigates financial integration between Islamic stocks and implied volatilities to become less positively related to harness diversification benefits.

However, as found by Karim et al. [25], Islamic stocks are less exposed to implied volatility or fear index than their conventional counterparts due to the former's distinct screening features to be more decoupled from the risks facing conventional markets. Conversely, Tissaoui and Azibi [24] and Shahzad et al. [26] documented that both Islamic and conventional stocks are exposed to global risk factors similarly and achieving strong linkages with their conventional counterparts. This leads to the rejection of the decoupling hypothesis of both Islamic and conventional stocks. These inconsistencies render a further assessment of the susceptibility of most Islamic stocks (Sharia-compliant) to several relevant implied volatilities worthwhile of examination to enhance investors' understanding and confidence.

It is known that implied volatilities drive interconnectedness among financial markets including Islamic stocks during stressful times [22]. What is not known is the susceptibility of Islamic stock returns to implied volatilities at market conditions of stress, normal, and boom using the quantile regression approaches? That is, prior studies conducted on the susceptibility of Islamic equities to implied volatilities are mostly silent on the use of the quantile regression approaches (see [20–24, 26]). However, the quantile regression approaches, quantile regression (QR), and quantile-on-quantile regression (QQR) offer the opportunity to capture the nonlinear, asymmetry, and nonstationary influence of changes in implied volatilities [13] and Islamic stock returns (see [27, 28]), as well as the effect during bearish, normal, and bullish market situations. The traditional QR and regular least squares approaches alone do not display these properties as good as QQR does. Furthermore, the market condition of Shariah stocks may not be the same as volatility indices. Thus, Shariah stocks and volatility indices may witness different market conditions and, hence, analysing the asymmetric relationships between the two assets across their varied market conditions is important.

We contribute to literature in three folds. First, we utilise aggregated Islamic stock indices from various blocs as a result of the heightened interactions among country level Islamic stocks. They include Dow Jones Islamic Market Asia-Pacific Developed TopCap Index (DJIMAPDI), Dow Jones Islamic Market Developed Markets Index (DJIMDI), Dow Jones Islamic Market World Emerging Markets Index (DJIMWEI), Dow Jones Islamic Market Europe Index (DJIMEI), Dow Jones Islamic Market World Index (DJIMWI), S&P Africa Frontier Shariah Index (S.PAFSI), and S&P Global 1200 Shariah (S.PGS). These Islamic stocks meeting the faith-based criterion are also considered as sustainable. The sustainability criterion of these indexes is in line with several initiatives of the establishment of the UN Principles for Responsible Investment in 2006, Global Initiative for Sustainability Ratings in 2011, Sustainable Stock Exchanges Initiative in 2012, UN Sustainable Development Goals in 2015, etc. There is, therefore greater expectations for

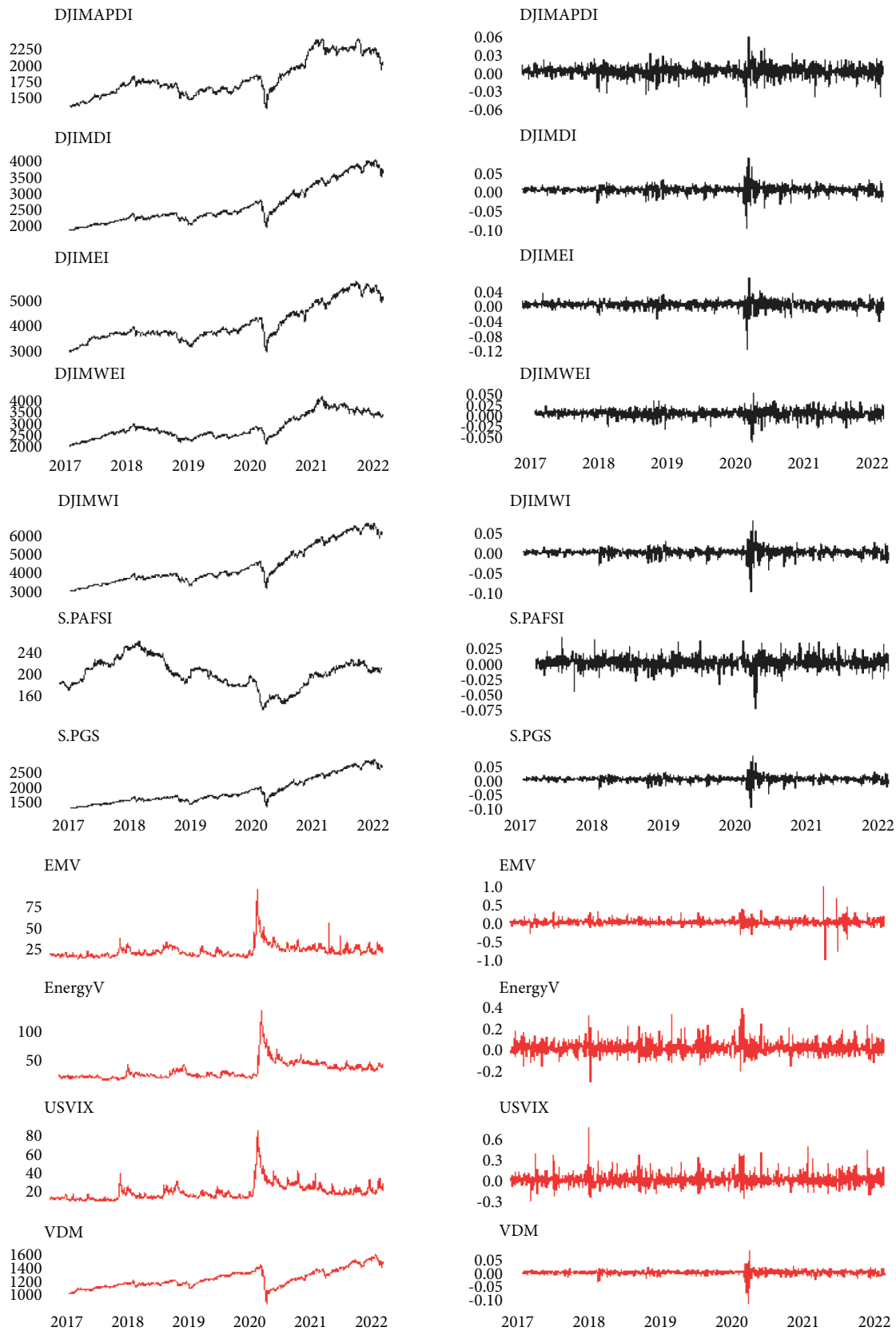


Figure 1: Price and returns series plots for Islamic stocks and volatility indices.

Table 1: Descriptive statistics.

	Mean	Median	Std. dev.	Skewness	Kurtosis	Jarque-bera	KPSS	TRS
DJIMAPDI	0.0003	0.0007	0.0097	−0.3156	6.7857	775.7587***	0.0856	12.8470***
DJIMDI	0.0006	0.0011	0.0106	−1.1688	21.4895	18292.5600***	0.0442	44.4930***
DJIMEI	0.0004	0.0010	0.0103	−1.4309	20.0821	15799.4600***	0.0509	10.8780***
DJIMWEI	0.0004	0.0008	0.0104	−0.7121	7.7362	1288.2020***	0.1061	18.3440***
DJIMWI	0.0005	0.0010	0.0102	−1.2406	21.5027	18354.7600***	0.0473	41.5920***
S_PGS	0.0006	0.0009	0.0105	−1.1214	21.1882	17687.6400***	0.0394	41.1870***
S_PAFSI	0.0001	−0.0002	0.0096	−0.3806	7.8655	1277.3060***	0.1636	1.2022
EMV	0.0002	−0.0058	0.0885	−0.0772	36.7427	59966.0800***	0.0116	159.8300***
ENERGYV	0.0005	−0.0042	0.0601	0.8925	7.1629	1080.4880***	0.0257	1.8618
USVIX	0.0007	−0.0072	0.0856	1.5055	11.4187	4210.1710***	0.0143	7.9395**
VDM	0.0003	0.0008	0.0095	−2.7244	44.8531	93818.7200***	0.0323	38.8090***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

firms around the globe to have a pivotal mandate to disclose their performance on sustainability issues while putting up a sustainable behaviour. However, since investors desire to form reliable portfolios, diversification benefits with other assets become their utmost flight to quality.

Second, the asymmetric effect of implied market volatilities which have gained significant interest from a nascent and fledgling body of academic literature is utilised in tandem with the sustainability Islamic stocks. We select four relevant implied market volatilities to integrate shocks from developed market, emerging market, the US market, and energy market. Most of these volatilities have been touted to be significant risk transmitters in several conventional assets [5, 13, 14, 18], but a few studies on Islamic stocks utilise specific or few implied volatility indices [20–22] to ensure a myopic view on the nexus. We do this to draw insights into effective portfolio reconstructions, redeployment, and rebalancing towards risk minimisation strategies.

Third, to examine the asymmetric effect of the implied market volatilities on Islamic stocks across market conditions (stress, benign, and boom) [29], the quantile regression as well as quantile-on-quantile regression techniques are employed. Moreover, the robustness of these estimates would hinge on the application of the causality in mean at various quantiles. These are presented to clearly divulge the heterogeneous [30] behaviour of markets and their participants across market conditions of stressed, normal, or boom [11, 31–34].

We found asymmetric influence of volatility on sustainable Islamic stock returns at various quantiles. Furthermore, most volatilities' asymmetric effects were negatively related to sustainable Islamic stock returns, implying diversification benefits across markets conditions. Moreover, with the exception of the extreme quantiles, there was a causal effect of implied market volatilities on Islamic stock returns at most quantiles.

The next of this section is arranged as follows. In Section 2, we present the study's methodology whereas Section 3 contains results and discussion. Section 4 concludes the study with some implications, recommendations, and suggestions for further studies.

2. Materials and Methodology

2.1. Data Sources and Description. We utilised daily data on Islamic stock indices for sustainability equities. The sustainability equities include; Dow Jones Islamic Market Asia-Pacific Developed TopCap Index (DJIMAPDI), Dow Jones Islamic Market Developed Markets Index (DJIMDI), Dow Jones Islamic Market World Emerging Markets Index (DJIMWEI), Dow Jones Islamic Market Europe Index (DJIMEI), Dow Jones Islamic Market World Index (DJIMWI), S&P Africa Frontier Shariah Index (S.PAFSI), and S&P Global 1200 Shariah (S.PGS). We utilised the seven Islamic stock indices because they are the top seven regarding market capitalisation aside meeting the interest-bearing debt threshold of 33% in accordance with the screening method of Dow Jones Sharia. This makes the indices relevant to withstand shocks and support diversification with other financial assets. All the seven indices are needed for this current study because they would provide better information on most Islamic sustainability or Sharia-compliant equities across different regional blocs to examine their susceptibility to shocks, while encouraging regional policy decisions.

Also, we used four implied volatilities to gauge investors' fear into the Islamic market. The implied volatilities are the CBOE Emerging Markets Etf Volatility (EMV), Chicago Board Exchange Volatility Index (USVIX), Dorsey Wright Developed Market Momentum and Low Volatility (VDM), and CBOE Energy Sector Etf Volatility (EnergyV). The four implied volatilities would comprehensively give us the opportunity to investigate their heterogeneous as well as asymmetric impact on the seven selected Islamic stocks for effective portfolio reconstructions, redeployment, and rebalancing towards risk minimisation strategies.

The daily data span 11th January, 2017 to 11th February, 2022, yielding up to 1264 observations. The suggested period was chosen based on the availability of consistent data at the start and the end locations. Regardless, this time period includes significant economic events such as the Brexit, crude oil price crash in history, and the COVID-19 pandemic. The data on sustainability Islamic equities were

Table 2: Unconditional correlation.

	DJIMAPDI	DJIMDI	DJIMEI	DJIMWEI	DJIMWI	EMV	ENERGYV	S_PAFSI	S_PGS	USVIX	VDM
DJIMAPDI	1.0000										
DJIMDI	0.4093***	1.0000									
DJIMEI	0.4726***	0.7133***	1.0000								
DJIMWEI	0.5780***	0.5859***	0.5884***	1.0000							
DJIMWI	0.4416***	0.9966***	0.7277***	0.6504***	1.0000						
EMV	−0.1278***	−0.5228***	−0.3953***	−0.3837***	−0.5287***	1.0000					
ENERGYV	−0.1841***	−0.6476***	−0.4816***	−0.4101***	−0.6487***	0.5818***	1.0000				
S_PAFSI	0.1460***	0.1570***	0.1730***	0.1264***	0.1595***	−0.0799***	−0.0697**	1.0000			
S_PGS	0.3982***	0.9950***	0.7056***	0.6002***	0.9935***	−0.5272***	−0.6512***	0.1505***	1.0000		
USVIX	−0.1070***	−0.6844***	−0.4293***	−0.3583***	−0.6778***	0.6085***	0.7346***	−0.0787**	−0.6857***	1.0000	
VDM	0.4711***	0.7963***	0.7250***	0.5166***	0.7989***	−0.3946***	−0.4650***	0.1760***	0.7940***	−0.4617***	1.0000

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 3: Effect of volatilities on DJIMAPDI.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.01575**	−0.02528***	−0.01011*	0.45535***
0.1	−0.01575**	−0.02528***	−0.01011**	0.47681***
0.15	−0.01575**	−0.02528***	−0.01011*	0.49609***
0.2	−0.01575**	−0.02528***	−0.01011**	0.49959***
0.25	−0.01575***	−0.02511***	−0.01011**	0.49959***
0.3	−0.01575***	−0.02511***	−0.01011***	0.49959***
0.35	−0.01575***	−0.02488***	−0.01011**	0.49959***
0.4	−0.01575***	−0.02488***	−0.01010**	0.49959***
0.45	−0.01575***	−0.02360***	−0.00920**	0.49959***
0.5	−0.01547***	−0.02360***	−0.00919**	0.49959***
0.55	−0.01547***	−0.02360***	−0.00919**	0.50519***
0.6	−0.01547***	−0.02302***	−0.00882**	0.51174***
0.65	−0.01547***	−0.02302***	−0.00882**	0.51951***
0.7	−0.01531***	−0.02302***	−0.00867**	0.52677***
0.75	−0.01531**	−0.02289***	−0.00867*	0.52831***
0.8	−0.01531**	−0.02289***	−0.00867*	0.52831***
0.85	−0.01531**	−0.02230***	−0.00832*	0.52831***
0.9	−0.01512**	−0.02230***	−0.00832*	0.52831***
0.95	−0.01512**	−0.02228***	−0.00832*	0.52831***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 4: Effect of volatilities on DJIMDI.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.06962***	−0.09963***	−0.07320***	0.88387***
0.1	−0.06962***	−0.09963***	−0.07320***	0.89498***
0.15	−0.06962***	−0.09963***	−0.07320***	0.89498***
0.2	−0.06926***	−0.09953***	−0.0730***	0.90393***
0.25	−0.06926***	−0.09937***	−0.07300***	0.90456***
0.3	−0.06926***	−0.09937***	−0.07289***	0.90823***
0.35	−0.06926***	−0.09924***	−0.07237***	0.91512***
0.4	−0.06926***	−0.09918***	−0.07237***	0.92651***
0.45	−0.06926***	−0.09918***	−0.07232***	0.93149***
0.5	−0.06926***	−0.09918***	−0.07210***	0.93149***
0.55	−0.06916***	−0.09918***	−0.07210***	0.93704***
0.6	−0.06916***	−0.09918***	−0.07210***	0.94197***
0.65	−0.06913***	−0.09918***	−0.07208***	0.94499***
0.7	−0.06913***	−0.09918***	−0.07208***	0.94505***
0.75	−0.06807***	−0.09843***	−0.07208***	0.94750***
0.8	−0.06786***	−0.09843***	−0.07208***	0.94925***
0.85	−0.06786***	−0.09830***	−0.07179***	0.95253***
0.9	−0.06786***	−0.09795***	−0.07179***	0.95336***
0.95	−0.06786***	−0.09795***	−0.07179***	0.95336***

Note. *, **, and ***, *** denote significance at 10%, 5%, and 1%, respectively.

obtained from RobecoSAM database. The volatility indices were obtained from investing.com. We utilised the natural logarithmic returns for each market indices.

2.2. Quantile-on-Quantile Regression (QQR). The conditional quantile link between two or more variables is empirically justified using the QQR technique, which is a non-parametric variant of the traditional quantile regression (QR). The QQR is suited for studying bearish and/or bullish interrelations between the returns on Islamic stocks and volatility indices since quantiles can express asymmetry among high and low logarithmic price patterns. We show susceptibility of the Islamic stocks to volatility indices which are non-parametrically expressed as

$$SR_t = \beta^{\theta}(VI_t) + u_t^{\theta}, \tag{1}$$

where SR_t and VI_t respectively, represent the returns of Islamic stock and volatility indices at period t, $\beta^{\theta}(\bullet)$ is the slope of the connection between the two assets at any

Table 5: Effect of volatilities on DJIMEI.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.04915***	−0.07023***	−0.04680***	0.83735***
0.1	−0.04915***	−0.07023***	−0.04680***	0.83735***
0.15	−0.04915***	−0.07016***	−0.04637***	0.84321***
0.2	−0.04915***	−0.07016***	−0.04637***	0.84402***
0.25	−0.04915***	−0.07016***	−0.04634***	0.86153***
0.3	−0.04915***	−0.06983***	−0.04582***	0.86656***
0.35	−0.04915***	−0.06957***	−0.04582***	0.86656***
0.4	−0.04915***	−0.06957***	−0.04562***	0.86656***
0.45	−0.04915***	−0.06957***	−0.04552***	0.86656***
0.5	−0.04915***	−0.06957***	−0.04552***	0.86656***
0.55	−0.04915***	−0.06957***	−0.04464***	0.86824***
0.6	−0.04915***	−0.06957***	−0.04442***	0.88414***
0.65	−0.04915***	−0.06927***	−0.04397***	0.88484***
0.7	−0.04915***	−0.06926***	−0.04397***	0.89459***
0.75	−0.04915***	−0.06926***	−0.04397***	0.90442***
0.8	−0.04886***	−0.06895***	−0.04347***	0.90672***
0.85	−0.04847***	−0.06895***	−0.04347***	0.91555***
0.9	−0.04847***	−0.06895***	−0.04347***	0.92350***
0.95	−0.04847***	−0.06895***	−0.04334***	0.92755***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 6: Effect of volatilities on DJIMWEI.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.05836***	−0.05987***	−0.03758***	0.55451***
0.1	−0.05836***	−0.05963***	−0.03747***	0.55451***
0.15	−0.05834***	−0.05963***	−0.03667***	0.55556***
0.2	−0.05834***	−0.05917***	−0.03667***	0.55675***
0.25	−0.05834***	−0.05790***	−0.03664***	0.55675***
0.3	−0.05830***	−0.0579***	−0.03651***	0.57460***
0.35	−0.05830***	−0.05726***	−0.03651***	0.58527***
0.4	−0.05830***	−0.05726***	−0.03651***	0.59868***
0.45	−0.05811***	−0.05726***	−0.03616***	0.59868***
0.5	−0.05811***	−0.05582***	−0.03616***	0.59868***
0.55	−0.05811***	−0.05582***	−0.03592***	0.59868***
0.6	−0.05811***	−0.05511***	−0.03552***	0.60408***
0.65	−0.05811***	−0.05479***	−0.03503***	0.60544***
0.7	−0.05811***	−0.05404***	−0.03452***	0.60544***
0.75	−0.05811***	−0.05384***	−0.03415***	0.60544***
0.8	−0.05811***	−0.05384***	−0.03413***	0.60609***
0.85	−0.05811***	−0.05384***	−0.03365***	0.60609***
0.9	−0.05811***	−0.05384***	−0.03365***	0.60609***
0.95	−0.05811***	−0.05384***	−0.03363***	0.60609***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

conditional level, the θth quantile of SR_t in equation (1) that is conditionally distributed is denoted by θ, and u_t^θ is the quantile in error which is made to have a θth conditional quantile.

By a first-order Taylor approximation of a quantile of SR^τ equations (1) is expanded to yield equation (2) as follows:

$$\beta^\theta(SR_t) \approx \beta^\theta(VI^\tau) + \beta^{\theta'}(VI^\tau)(VI_T - VI^\tau), \tag{2}$$

where the partial derivative of $\beta^\theta(SR^\tau)$ is explained by $\beta^{\theta'}$, representative of a marginal effect as the slope. It is depicted that θ is the functional illustration of $\beta^\theta(SR^\tau)$ and $\beta^{\theta'}(VI^\tau)$, from equation (1), while τ is the functional illustration of VI and VI^τ also in respect of equation (2). Therefore, θ and τ are the functional representations of $\beta^\theta(VI^\tau)$ and $\beta^{\theta'}(VI^\tau)$, is for equation (2). By substituting each of $\beta^\theta(VI^\tau)$ and $\beta^{\theta'}(VI^\tau)$ from equation (2) for $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ we deduce equation (3) as

Table 7: Effect of volatilities on DJIMWI.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.06769***	−0.09822***	−0.07147***	0.85924***
0.1	−0.06769***	−0.09802***	−0.07146***	0.86302***
0.15	−0.06769***	−0.09802***	−0.07146***	0.86791***
0.2	−0.06769***	−0.09802***	−0.07146***	0.87351***
0.25	−0.06769***	−0.09802***	−0.07130***	0.87520***
0.3	−0.06733***	−0.09802***	−0.07094***	0.88179***
0.35	−0.06733***	−0.09637***	−0.07094***	0.88179***
0.4	−0.06712***	−0.09637***	−0.07071***	0.88208***
0.45	−0.06712***	−0.09637***	−0.07071***	0.88565***
0.5	−0.06712***	−0.09628***	−0.07061***	0.88935***
0.55	−0.06708***	−0.09628***	−0.07009***	0.90236***
0.6	−0.06708***	−0.09586***	−0.07009***	0.90901***
0.65	−0.06708***	−0.09586***	−0.06969***	0.91342***
0.7	−0.06708***	−0.09568***	−0.06962***	0.91669***
0.75	−0.06708***	−0.09568***	−0.06962***	0.91669***
0.8	−0.06708***	−0.09568***	−0.06927***	0.91729***
0.85	−0.06708***	−0.09568***	−0.06896***	0.91848***
0.9	−0.06703***	−0.09553***	−0.06896***	0.92212***
0.95	−0.06703***	−0.09553***	−0.06894***	0.92212***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 8: Effect of volatilities on S.PAFSI.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.00658	−0.01063*	−0.00710*	0.07300
0.1	−0.00658	−0.01063*	−0.00710**	0.07300
0.15	−0.00632	−0.01063*	−0.00710*	0.07660
0.2	−0.00605	−0.01049*	−0.00683**	0.09160*
0.25	−0.00605	−0.01049**	−0.00674**	0.09160**
0.3	−0.00605	−0.01049**	−0.00674*	0.09958**
0.35	−0.00601*	−0.01049**	−0.00674**	0.10170**
0.4	−0.00601*	−0.01049**	−0.00674**	0.10275**
0.45	−0.00601*	−0.00989**	−0.00657*	0.10794***
0.5	−0.00601*	−0.00938**	−0.00657**	0.12050***
0.55	−0.00601*	−0.00926**	−0.00627*	0.12050***
0.6	−0.00601*	−0.00895**	−0.00627*	0.12050***
0.65	−0.00601*	−0.00895**	−0.00627**	0.12050***
0.7	−0.00601	−0.00888*	−0.00627*	0.12050***
0.75	−0.00601	−0.00885*	−0.00627*	0.12050***
0.8	−0.00601	−0.00885*	−0.00627*	0.12261***
0.85	−0.00601	−0.00885*	−0.00574	0.12856***
0.9	−0.00601	−0.00856	−0.00544	0.14270***
0.95	−0.00601	−0.00856	−0.00544	0.14475***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

$$\beta^{\theta}(SR_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(VI_T - VI^{\tau}). \quad (3)$$

Equation (2) can now be substituted into equation (1) to arrive at equation (4) as

$$SR_t = \beta_0(\theta,\tau) + \beta_1\left(\underbrace{\theta}_{(*)},\tau\right)(VI_T - VI^{\tau}) + u_t^{\theta}, \quad (4)$$

where $(*)$ yields the conditional quantile of θth of returns on VI in equation (4). It additionally portrays the true susceptibility of the $SR(\tau th)$ to shocks from the quantile of the $VI(\theta th)$ in respect of equation (4), of the parameters β_0 and β_1 with indices represented by θ and τ.

Similar to the case of OLS, we apply an analogous minimisation to produce the following equation

$$\min_{b_0,b_1}\sum_{i=1}^{n}\rho_{\theta}\left[SR_t - b_0 - b_1\left(\widehat{VI}_t - \widehat{VI}^{\tau}\right)\right]K\left(\frac{F_n\left(\widehat{VI}_t\right)-\tau}{h}\right), \quad (5)$$

where the quantile loss function, $\rho_{\theta}(u)$, is represented as $\rho_{\theta}(u) = u(\theta - I(u<0))$, i is the function of indicator, the

Table 9: Effect of volatilities on S.PGS.

Quantiles	EMV	EnergyV	USVIX	VDM
0.05	−0.06820***	−0.10178***	−0.07244***	−0.07244***
0.1	−0.06820***	−0.10178***	−0.07244***	−0.07244***
0.15	−0.06769***	−0.10178***	−0.07244***	−0.07244***
0.2	−0.06769***	−0.10148***	−0.07243***	−0.07243***
0.25	−0.06769***	−0.10148***	−0.07241***	−0.07241***
0.3	−0.06769***	−0.10148***	−0.07234***	−0.07234***
0.35	−0.06769***	−0.10148***	−0.07176***	−0.07176***
0.4	−0.06769***	−0.10148***	−0.07176***	−0.07176***
0.45	−0.06769***	−0.10148***	−0.07176***	−0.07176***
0.5	−0.06769***	−0.10119***	−0.07176***	−0.07176***
0.55	−0.06769***	−0.10075***	−0.07175***	−0.07175***
0.6	−0.06705***	−0.10075***	−0.07172***	−0.07172***
0.65	−0.06705***	−0.10053***	−0.07172***	−0.07172***
0.7	−0.06705***	−0.10028***	−0.07165***	−0.07165***
0.75	−0.06705***	0.09946***	−0.07165***	−0.07165***
0.8	−0.06705***	0.09946***	−0.07164***	−0.07164***
0.85	−0.06705***	0.09946***	−0.07164***	−0.07164***
0.9	−0.06702***	0.09946***	−0.07164***	−0.07164***
0.95	−0.06702***	0.09946***	−0.07164***	−0.07164***

Note. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

kernel density function (KDF) is denoted as $K(\bullet)$, and h is the bandwidth parameter of the KDF. The observations of VI^{τ} is weighted by the KDF where the minimal weights are inversely connected to the distribution of $\widehat{VI}_t$ in the form of $F_n(\widehat{VI}_t) = (1/n)\sum_{k=1}^{n} I(\widehat{VI}_k < \widehat{VI}_t)$.

Following the specifications of Sim and Zhou [35], the bandwidth for the quantiles we employ in this study for the QQ breakdown is defined as $h = [0.05 \text{ to } 0.95]$. The smoothness of the estimated results is contingent on the bandwidth, which represents the divisions of the quantiles. Smaller bandwidths are recommended over larger bandwidths because larger bandwidths may lead to biased estimates of the coefficients.

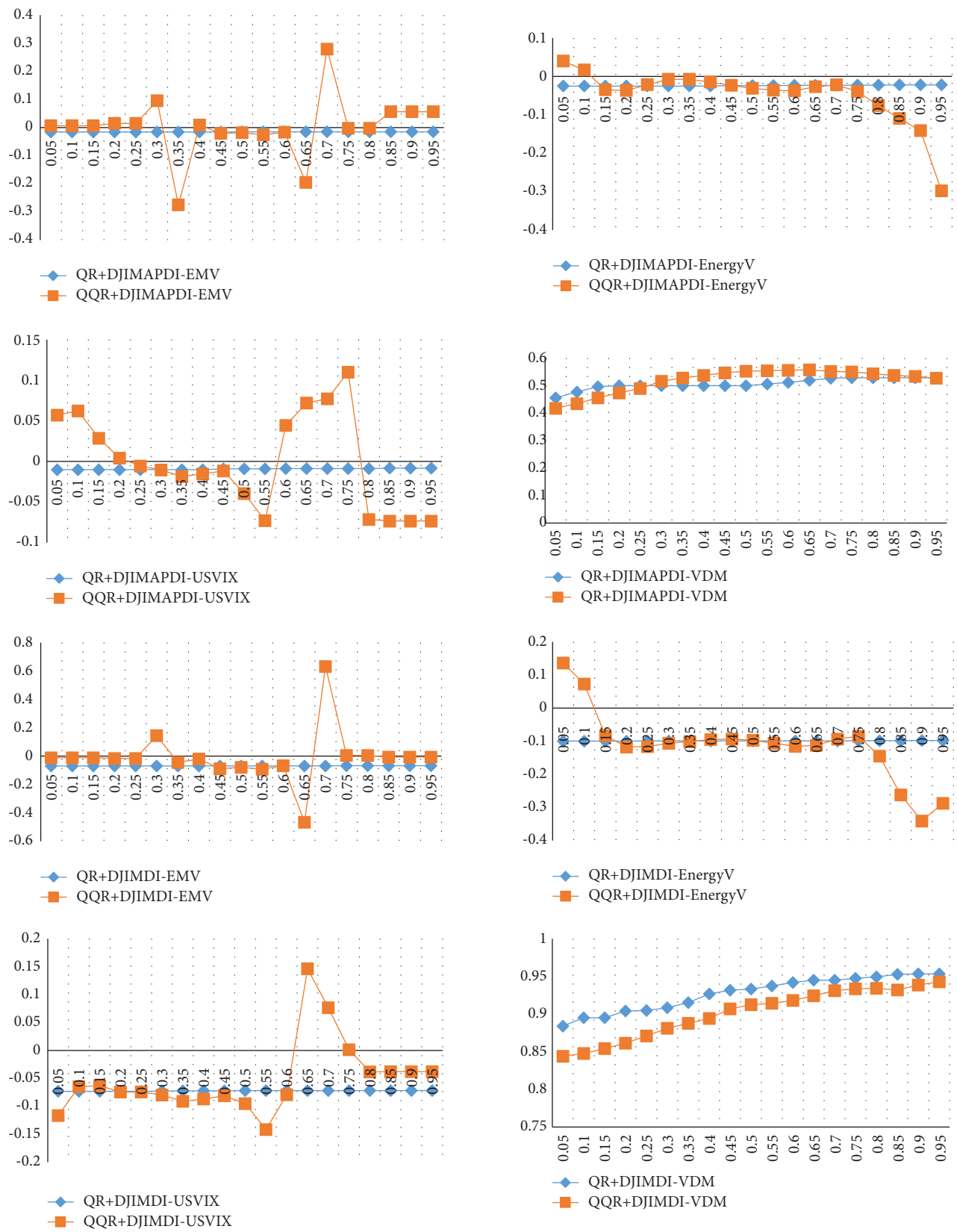
3. Results and Discussion

3.1. Preliminary Analysis. The time series plots of both price and returns for sustainable Islamic stocks (in black) and volatility indices (in red) are presented in Figure 1. Most of the Islamic stocks trend upwards prior to mid-2020, plunge in the mid-2020, and skyrocketed afterwards. It can be observed that markets rebound after the COVID-19 pandemic, demonstrating high market performance, supersede that of prior to the pandemic. Accordingly, we find prospects of extreme markets rebound after the onset of a shock within the sustainable Islamic stock markets. Conversely, except for the developed market volatility index, the remaining volatility indices are inversely related to the Islamic stock market, indicating a potential hotspot for portfolio diversification, hedge, or safe haven. Also, the plunge in prices at the COVID-19 pandemic is shown as shocks in the returns plots of the sustainability Islamic stocks. Generally, all the returns series exhibit volatility clustering.

We present Table 1 to examine the behaviour of individual financial time series over the sampled period. It can be seen that all the variables have positive mean suggesting potential for increased market performance. Also, there are fewer variations in the data and tendency for more negative values than higher values in addition to a leptokurtic distribution. We confirm that the data distribution of all financial time series demonstrates non-normality from the Jarque-Bera statistics.

Additionally, we observe from the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test that all the returns series are stationary with a failure to reject the null hypothesis of stationarity (p-value > 0.05). However, since all the returns series are not normally distributed, it accentuates the relevance of employing an asymmetric statistical tool capable of revealing relationships across market situations. In assessing the linearity of the financial time series, the Teraesvirta's Neural Network (TRS) test with a null hypothesis of linearity is employed. The TRS test suggests that the original returns series are nonlinear (p-value < 0.05). This further addresses the need for employing the QQR technique which is able to effectively deal with issues of asymmetry and nonlinearity relative to the traditional QR and OLS (see, e.g., [36] and references therein).

Moreover, the unconditional correlation coefficients between two time series are shown in Table 2. It is clear that the correlation of all the financial time series are almost significant at the 1% level. We notice a mixture of positive and negative correlations ranging from small to large magnitudes. The negative relationships between the variables have high likelihood for diversification, and this can be found between the Islamic stock returns and most of the volatility indices. This implies that portfolio diversification



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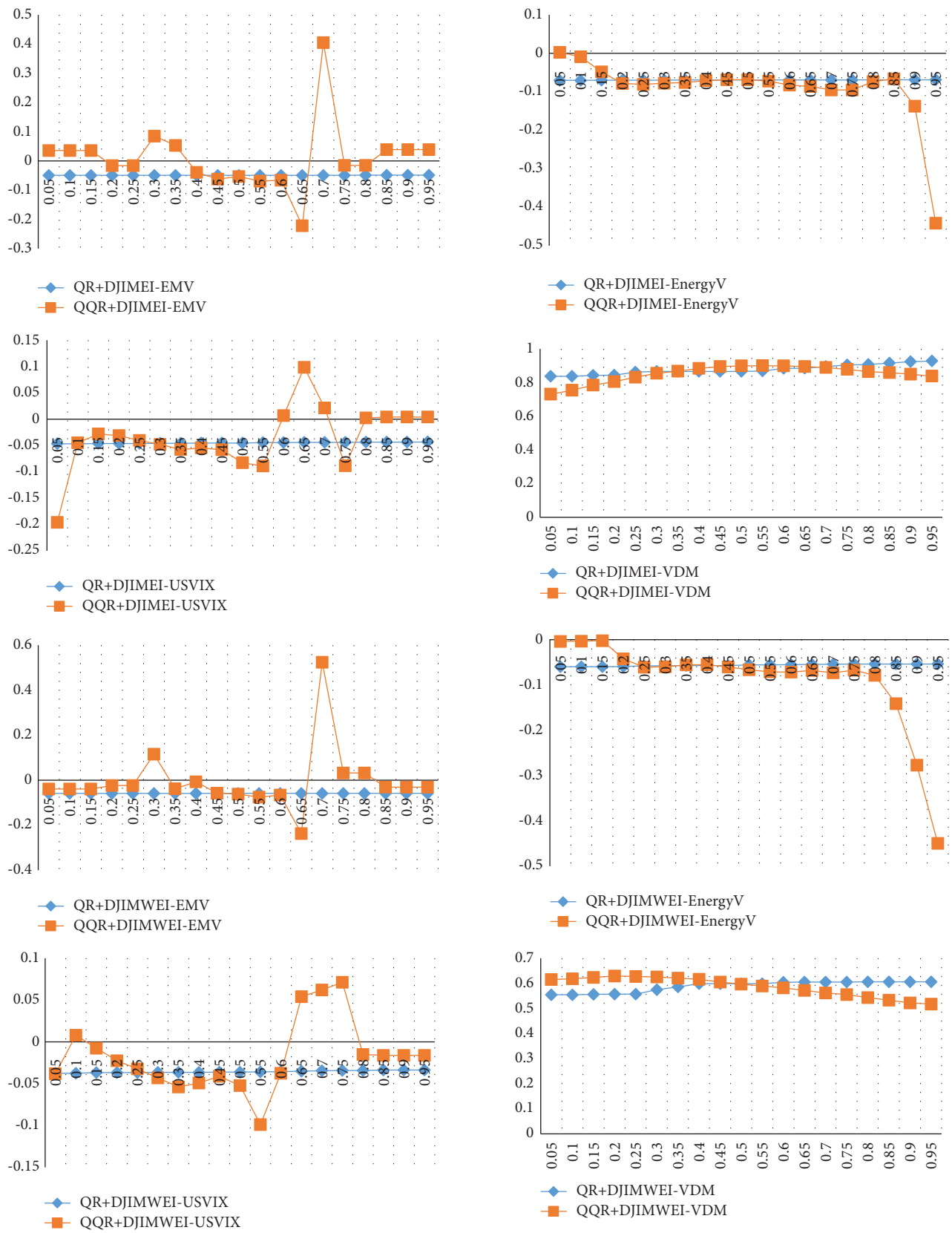

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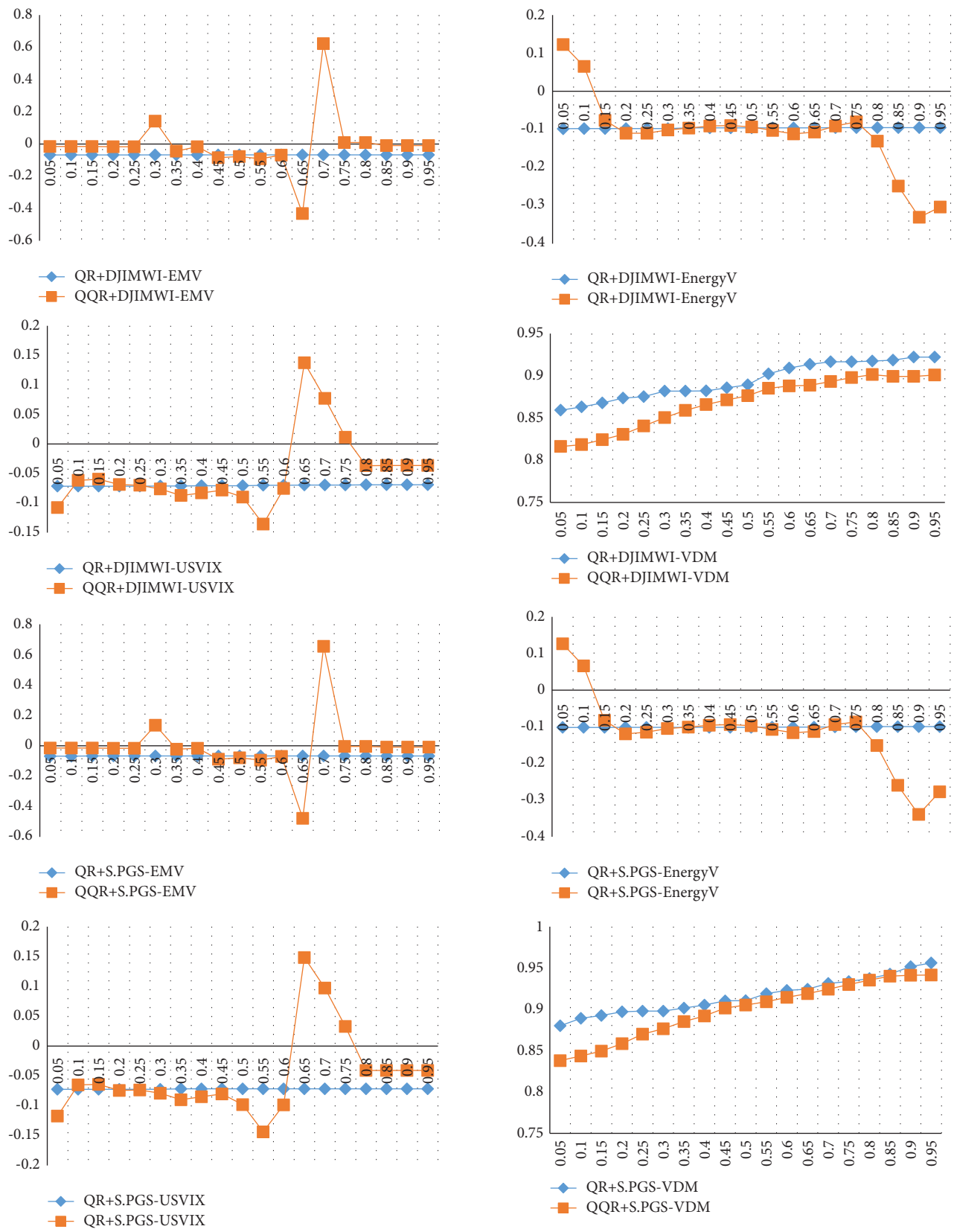

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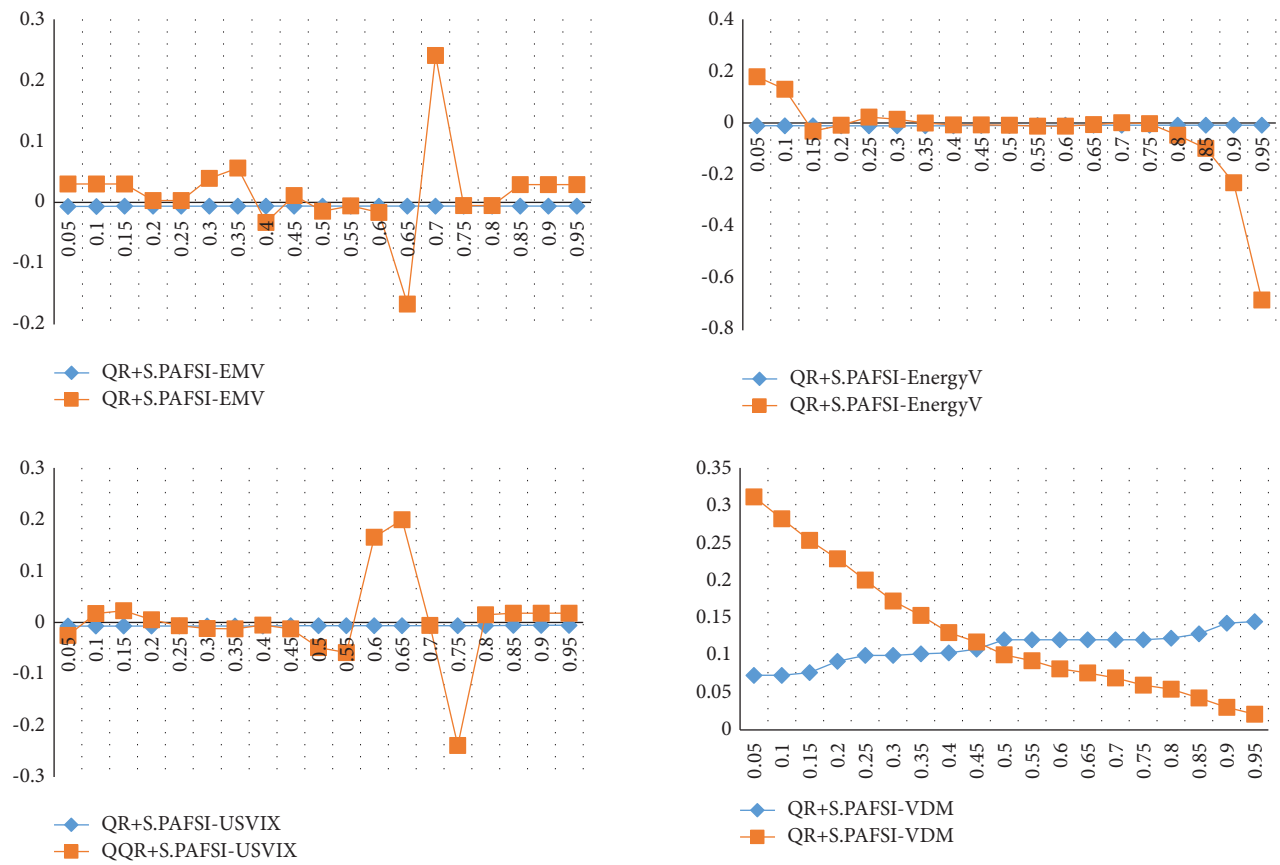


(d)

Figure 2: Comparison plots of QR and QQR.

among the sustainability Islamic stocks would do more harm than good to potential investors.

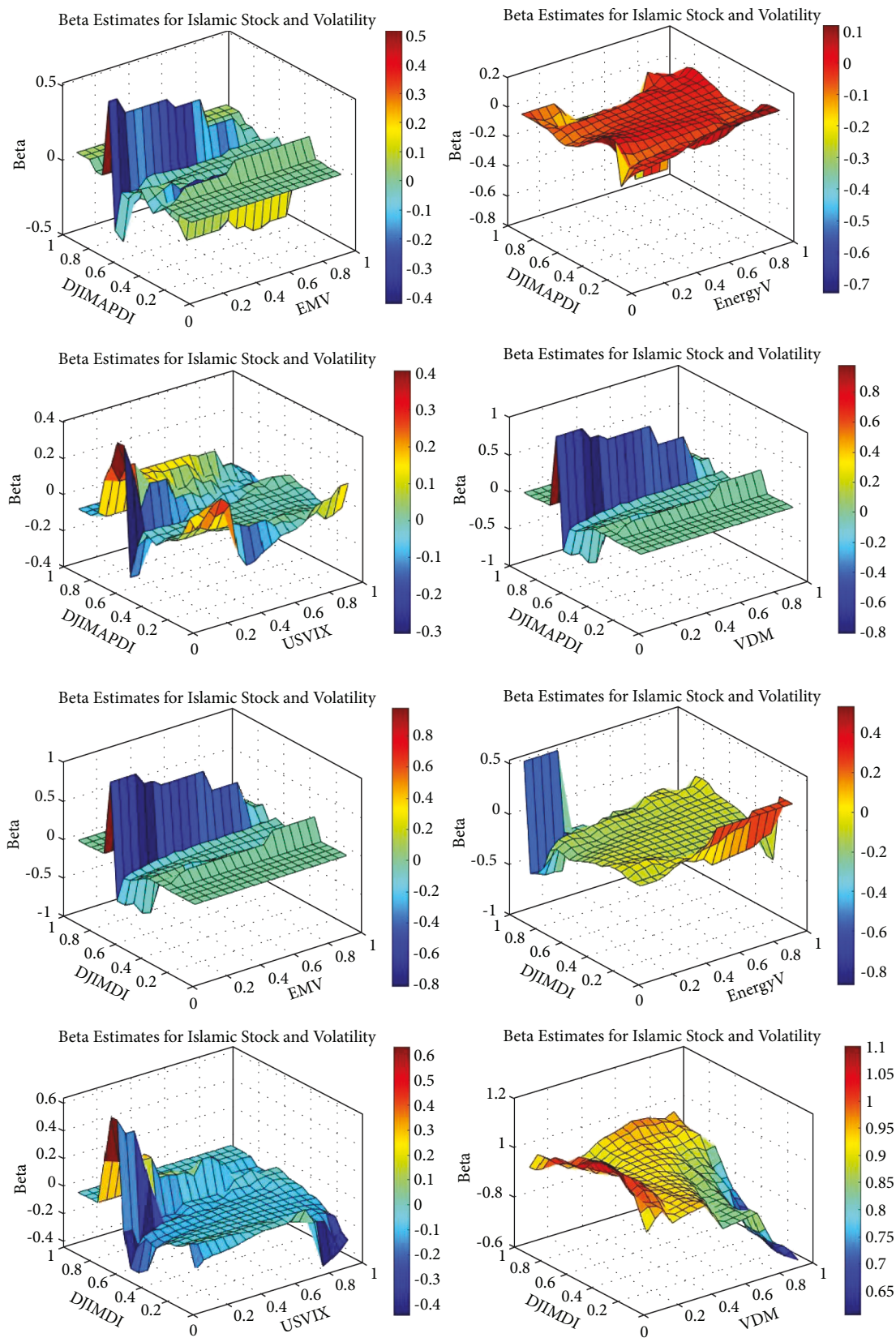
3.2. Quantile Regression. Tables 3–9 present the asymmetric effect of implied market volatilities on sustainable Islamic equities. We find a significant effect of implied market volatilities on Islamic stock returns across quantiles at varying levels of significance. The susceptibilities of Islamic stock returns to market volatilities across market conditions (stressed, benign, and boom) are mostly negative, except for volatilities from developed markets. Surprising, the effect of developed market volatilities on Islamic stocks have large magnitude, and considered to be positive except for S.PGS from Table 9. The similar asymmetric coefficients at most markets conditions demonstrate the persistence of Islamic stocks to external shocks. This explains that it takes a while for Islamic stocks to respond to changes in shocks from external shocks.

Comparatively, all volatility indices but developed market volatility demonstrate reduction in magnitudes from the lower quantile to the upper quantile. Suggesting that negative shocks are more prominent at stressed market outcome, whereas positive shocks are stronger at market boom for all Islamic equities. It can therefore be concluded that most sustainable Islamic stocks are vulnerable to implied market volatilities.

This is partly in line with the assertion made by Haddad et al. [23] that Islamic equities are susceptible to international shocks. The significant negative effect of implied volatility from the energy market concurs with the findings of Karim and Masih [20] and Lin and Su [21]. Conversely, Lin and Su [21] found that negative shocks between implied volatility from crude oil and Islamic stocks are more prominent at higher quantiles. Moreover, outcomes generated from the current study do not absolutely deviate from the ones generated by prior studies on conventional assets as well as commodities [5, 13, 14, 18].

It is relevant that investors of Islamic stocks form a well diversifiable portfolio with market volatilities. Also, existing investors of sustainable Islamic stocks should hedge against fluctuations in Islamic stocks having in mind the behaviour of market volatilities or redistribute their existing Islamic stock portfolios.

3.3. QQR and QR Comparison. In this section, we investigate the relevance for a non-parametric asymmetric distribution among the sustainable Islamic stock returns and volatilities returns. It also gives the opportunity to infer how significant the QQR estimates are, having the knowledge of the QR estimates. Figure 2 presents the combined plots for both QQR and QR. A look at Figure 1 indicates that although



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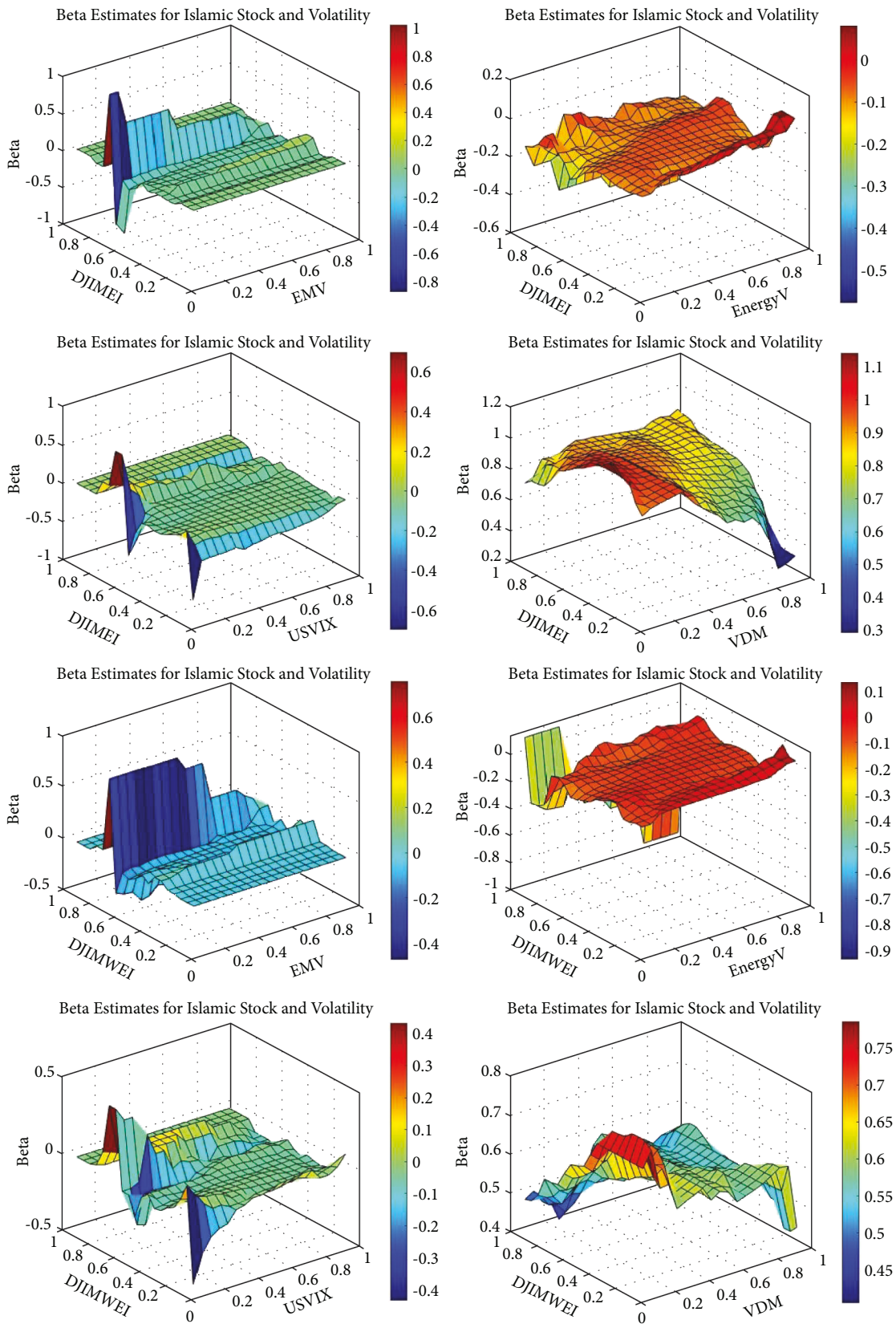

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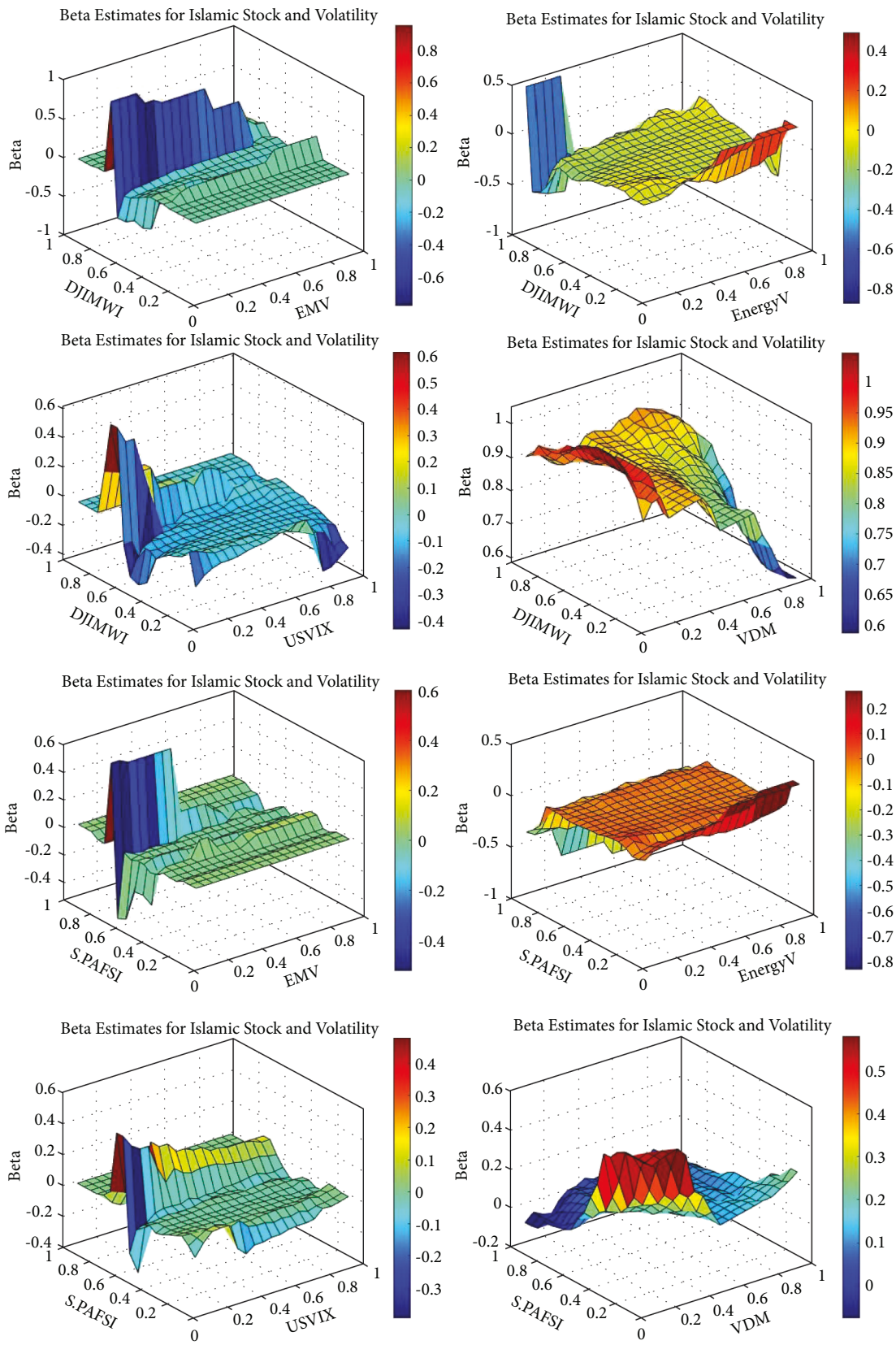

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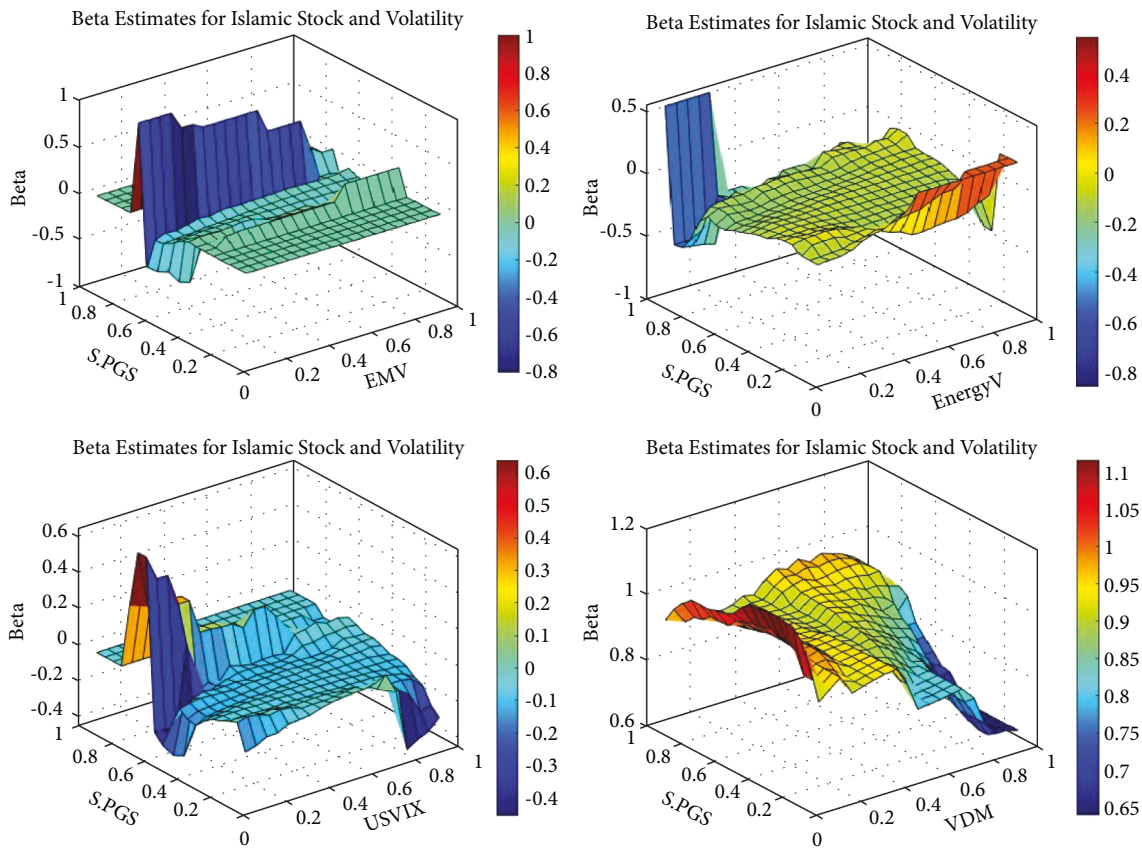


(d)

Figure 3: QQR plots for Islamic stocks and volatility indices.

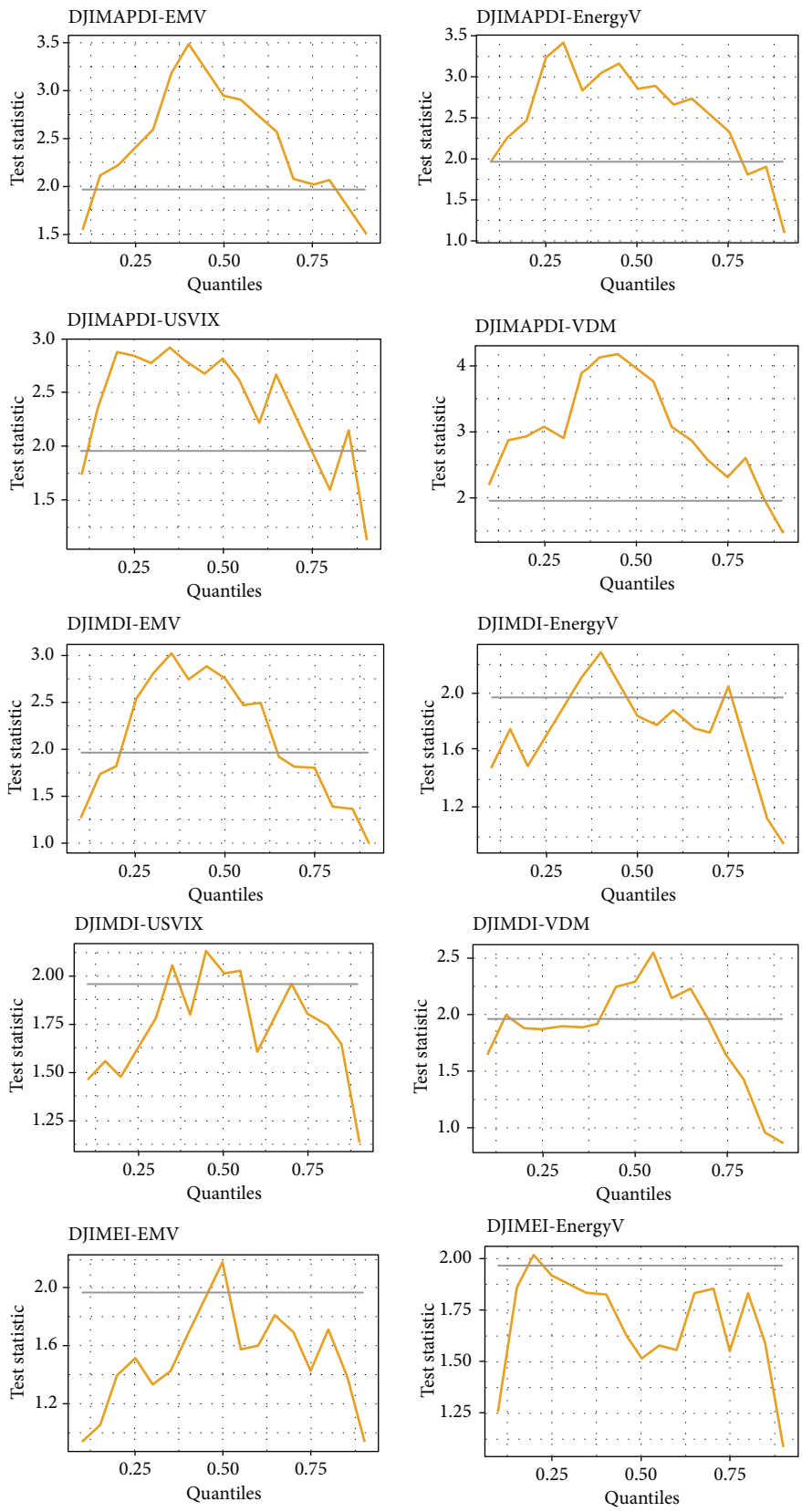
most of the QQR estimates are not mirror images of the QR estimates, they are a little closer to each other. The reason why the line graphs are not mirror images of each other could be due to the presence of different information contained in the asymmetric distributions of both Islamic and implied volatilities simultaneously as addressed by the QQR alone (see [21, 27, 28]). Nonetheless, to some extent, the line graphs confirm the QQR except for the extreme quantiles of most relationships.

It is worth noting that relative to the QR, the QQR projects a better view of the asymmetric linkages among the dependent and independent variables at varied quantiles of both variables. Hence, given that majority of the QQR estimates are confirmed by their QR counterparts, we emphasise the relevance of the chosen methodological framework. We present the three-dimensional QQR estimates in the next subsection to further address the asymmetric and nonlinear dynamics of the employed financial time series.

3.4. Quantile-on-Quantile Regression. The three-dimensional asymmetric dependent nexus among Islamic stock returns and implied market volatilities is shown in Figure 3. It can be observed that lower values leading to negative values relative to higher ones are persistent with emerging market volatility and the US VIX. This implies that considering the quantile dependence structure of both Islamic stocks and implied market volatilities, it is better to diversify with the emerging market volatility and the US VIX. Accordingly, having in mind of the quantile dependence structure of the possible combinations of this study, portfolio rebalancing or redeployment is pertinent with volatilities from the energy and developed markets.

3.5. Robustness. The causality in mean, as proposed by Jeong et al. [37] and advanced by Balcilar et al. [38] is employed in this study to confirm if sustainability Islamic stock returns are significantly driven by volatilities at varying levels of market conditions. Prior empirical research investigating the resilience of quantile regression has used this approach (see [13, 39]).

Figure 4 shows that, with the exception of the S&P Africa Frontier Shariah Index, volatility indexes have a strong causal impact on sustainable Islamic stock returns. From the lower mid quantiles to the upper mid quantiles, the causation grows stronger. This means that typical market outcomes influence causal estimates for our quantile regression model more than market stress and boom.



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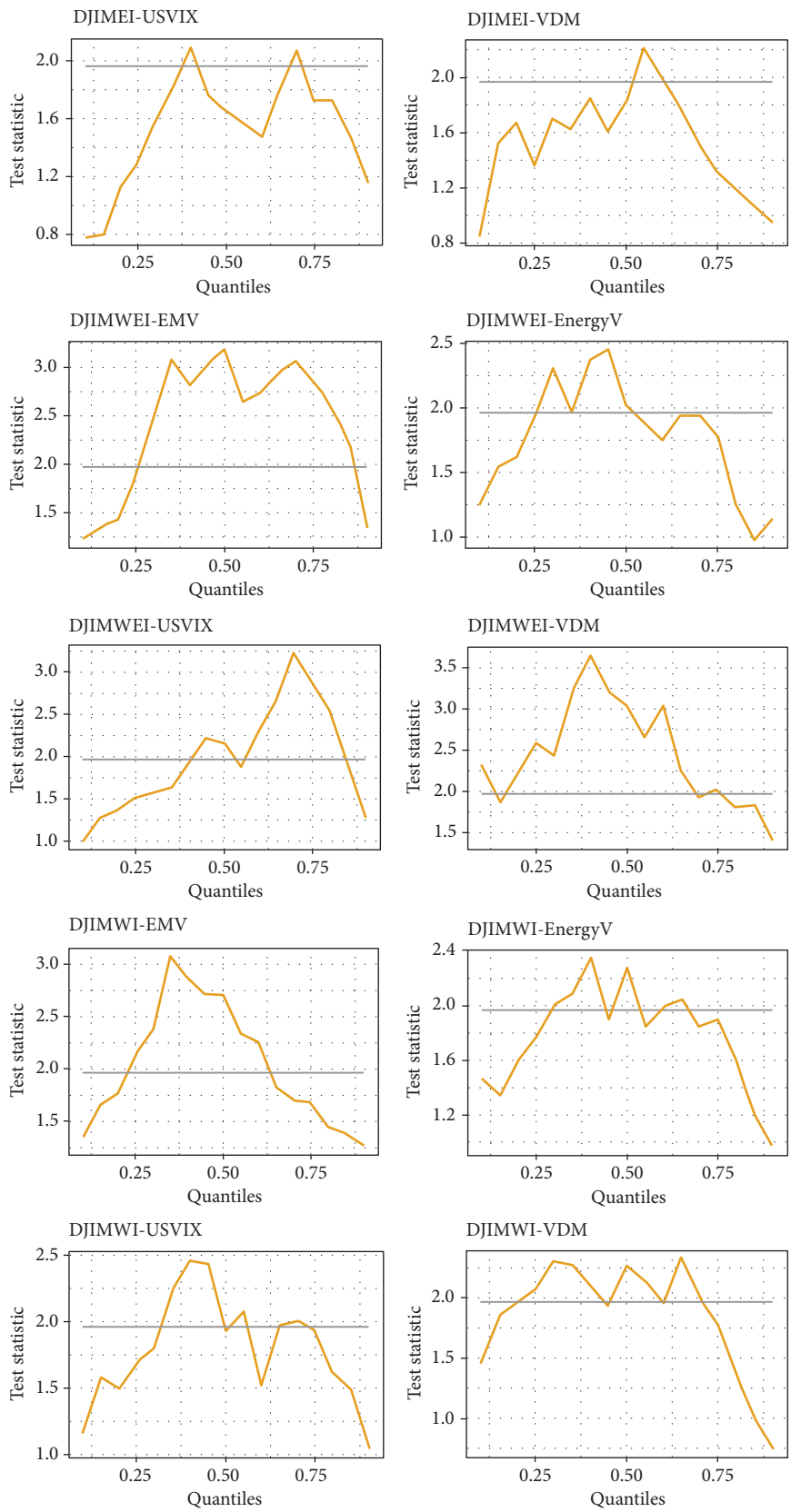

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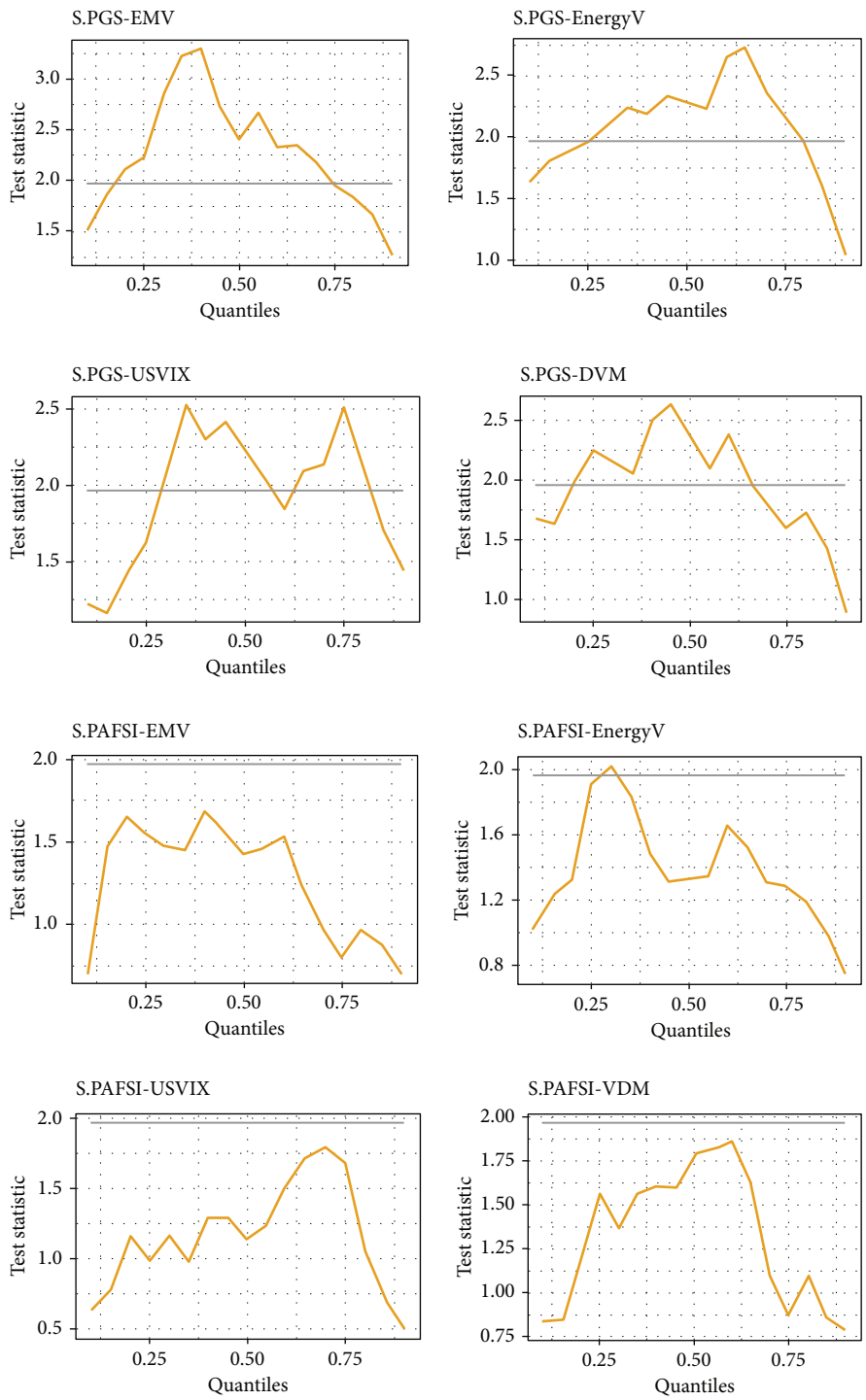

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Figure 4: Causality in mean at various quantiles.

4. Conclusion

We contribute to the asymmetric relationship among sustainability Islamic stock returns and volatility returns across market conditions. Hence, the quantile regression and quantile-on-quantile regression techniques were employed. The causality in mean technique at various quantiles was further utilised to examine the robustness of our quantile estimates.

Findings from the study revealed asymmetric effect of volatilities on sustainability Islamic stock returns at various quantiles. In addition, the asymmetric effects of most

volatilities were mostly inversely related with sustainability Islamic stock returns, suggesting diversification benefits at various markets outcome. Also, we document causality from volatility to Islamic stocks at various quantiles, except for the extreme quantiles. It goes to reason that typical market outcomes influence causal estimates for our quantile regression model more than market stress or boom.

Particularly for each volatility indexes, volatility index from developed markets transmits positive shocks to sustainability equity indices, except for the S&P Global 1200 Shariah (S.PGS). Hence, diversification benefit would manifest only with the S.PGS index from shocks from the developed market volatility index. On the other hand, the remaining volatility indices transmit negative shocks at various quantiles indicating the need to diversify, hedge, or seek safe haven from them. The significant asymmetric relationship among Islamic stock returns and implied market volatilities across quantiles demonstrates inefficient market dynamics exacerbated by the irrational behaviour of investors to accentuate the heterogeneous and adaptive market hypotheses.

It is recommended that existing and potential investors of sustainable Islamic stocks be mindful of the heterogeneous susceptibilities of these stocks to market volatilities. It is important that they study the market at various markets condition, having in mind the potency of market volatilities. It is necessary that optimal policy interventions from these sustainable Islamic regional blocs are deployed to revamp vulnerable Islamic markets to external shocks. Further studies can assess frequency-dependent asymmetric impact of market volatilities on sustainability stocks at various investment horizons and market outcomes [12, 40, 41].

Data Availability

The data used to support this study are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Situated Information Flow between Food Commodity and Regional Equity Markets: An EEMD-Based Transfer Entropy Analysis

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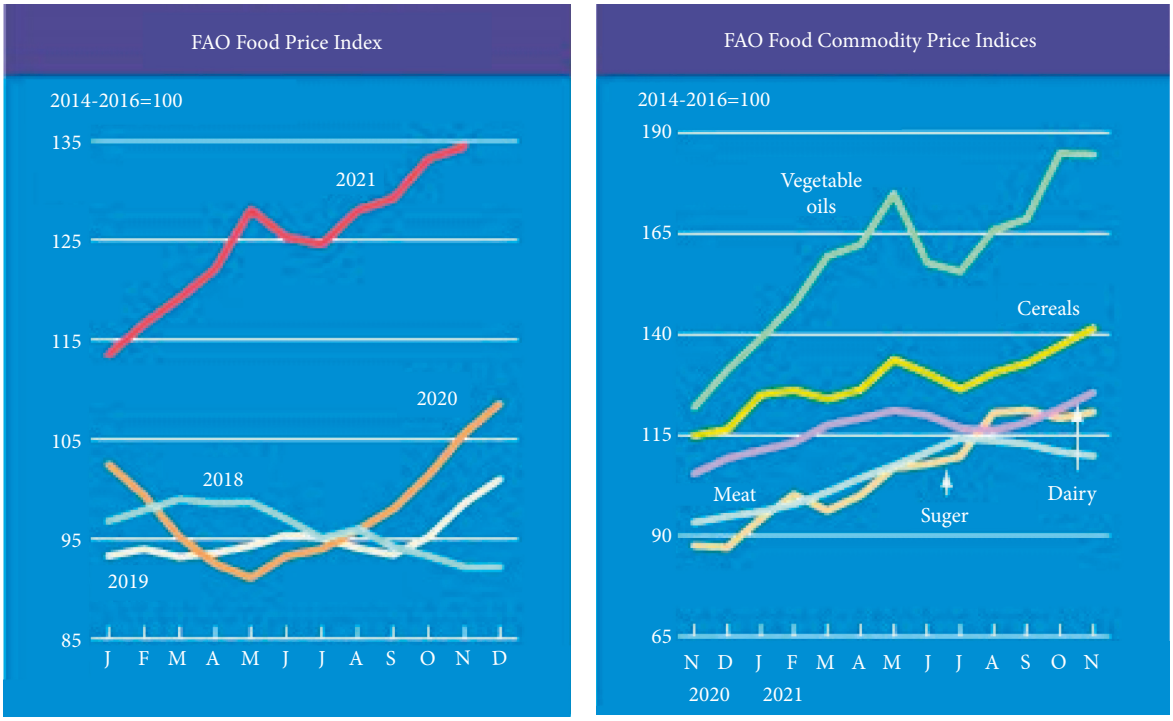
The intrinsic information shared by financial assets provides a means of assessing their mutual linkages. In times of crisis, spillovers and information flow between markets increase, and this drives empirical investigations into the degree of connectedness between financial assets. In the context of commodity markets, empirical evidence about the mutual information shared and its influence on portfolio management is largely unknown. This study examines the situated information between the food commodities (cereals, dairy, food, meat, vegetable oil, and sugar) of the FAO and regional stock markets' returns. From the ensemble empirical mode decomposition (EEMD)-based Rényian transfer entropy analysis employed, we find significant bidirectional information flow between the food commodities and regional equity markets. Our findings divulge that the diversification potentials of food commodities rest in the long term, with sugar being a consistent diversifier across all investment horizons. The investment and policy implications of our findings are further discussed.

1. Introduction

The markets for agricultural commodities have had a remarkable linkage with each other in recent years, with major swings and drastic changes. Agricultural commodity prices may fluctuate a lot; therefore, hedging against their negative fluctuations, for example, through futures markets, become a major and crucial responsibility for market players. Price volatility will not only drive anomalies in agricultural markets but also result in higher expenditure for exporters, importers, and individual customers. This makes the market unreliable because accurate economic forecasts of the future will be impossible, deterring both present and prospective investors [1, 2].

Food security for poorer households may be jeopardised by a major transmission of growing worldwide food prices [3], and volatility in these food prices may ultimately impact the poor, especially in countries with little or no agricultural warehouses [1]. It is worth emphasising that food price rises have not been uniform over the world and that these agonising increases in food costs have disproportionately impacted the poor, particularly in agriculturally reliant nations, where staple foods account for a major share of income [2].

Records from the Food and Agriculture Organisation (FAO) indicate that for almost over a decade, the food price index (FPI) of FAO reached its highest level in October 2021 and continued to increase in November 2021 [4]. A complete picture of the recent trajectories in the FPI and its constituent commodities is shown in Figure 1. FAO's FPI comprises indices of five key commodities, namely cereals, dairy, meat, vegetable oil, and sugar. The FPI is a monthly assessment of the change in worldwide food commodity prices consisting of 23 commodities and their subcategories.



(a) (b)

Figure 1: Trajectories of FAO indices for FPI (a) and its constituents (b) (source: FAO [4]).

The price movement in multiple commodities is tracked and endogenously determined by each of these indicators. The cereals price index, for example, reflects changes in worldwide wheat, maize/corn, and rice prices. This gives a broad spectrum for analysis.

These commodity indices have experienced historical trends in the COVID-19 era. For instance, FAO [4] reports that wheat prices rose for the fifth month in a row, reaching their highest level since May 2011. More recently, "the FAO Dairy Price Index averaged 132.1 points in January, up 3.1 points (2.4%) from December 2021, marking the fifth consecutive monthly increase, and placing the index 20.8 points (18.7%) above its value in the corresponding month last year" [5]. Several dynamics in the FAO FPI and commodity price indices have been witnessed since the emergence of the COVID-19 pandemic. On top of these revelations about food commodity prices, the United Nations Economic Commission for Africa (UNECA) [6] has cautioned against the persistence of volatilities in food commodity prices in the COVID-19 era. It is noteworthy that recent developments in food commodity prices are suggestive of their linkages.

One of the main reasons why returns and volatility in agricultural markets might be linked is that because economies are intertwined through trade and investment, any news concerning supply and demand in one country has ramifications for the others [7]. Hedgers and speculators in international markets, for example, are widely known for basing their judgments on information generated locally and from foreign markets [7, 8]. During the COVID-19 pandemic, spillovers and information flow between the markets—both commodities and equities—intensified [8, 9]. Furthermore, in recent decades, the increasing attention on commodity markets' financialisation has caused significant changes in some fundamental relationships between commodities and traditional assets such as stocks and bonds [10, 11]. From the above arguments, we propose that studies on commodities focus on a new direction that examines information flow between commodities and global equities to inform international portfolio management.

The sources of volatilities among food prices [12], the effect of market crises on food prices [1, 13, 14], comovement, and drivers of food price connectedness [3, 15] have been examined, but information flow has been left out. Specifically, information flow between food commodities and stock markets has not yet received scholarly attention. Nonetheless, the importance of this strand of empirical literature cannot be underestimated, as explained in the previous paragraphs. Theoretically, a measure of information vis-à-vis the driving and responding flow for multiple time-variant variables could be determined. Schreiber [16] defines this as transfer entropy (TE).

Based on the philosophical principles of Dretske [17] and Pearl's [18] statistics, the quantification of the intrinsic information flow between two random time series variables is made possible. This forms the foundation of the situated information flow theory (SIFT) [19]. The SIFT advocates that causality between financial markets could be retrieved from the common information they share. Consequently, if there is the mutual information between two random time series, their relationship could be inferred by analysing how the state of one of the variables is learnt by the other through

observation [8, 9, 20–25]. In the context of this study, the dynamics in either market (commodity or stock) could influence the other. Therefore, a two-way flow, where stocks could observe the behaviour of commodities and vice versa through the commonly shared inherent information, is considered.

Furthermore, we propose that since economies are intertwined through investment and trade, any news concerning pricing, supply, and demand of commodities, together with news from the regulation of regional or national stock markets, have ramifications for the others [1, 7]. Financial market hedgers and speculators across the globe, for example, are widely known for making judgments based on both locally and internationally generated information [7, 26]. Thus, a quantification of the mutual information between these markets is important for policy management, asset allocation, risk-taking, and portfolio management. This influences the use of transfer entropy to examine the causal relationships between commodities and stocks in the global market space.

Notwithstanding, evidence from the empirical literature [8, 9, 20–25, 27] suggest that the flow of information and investor response to such information is not only time-dependent but also varies across frequencies. It is instructive to note that frequency-domain analysis is a significant component for investors who operate at different time horizons [28–37]. Moreover, the stylised facts of fat tails and volatility clustering of financial time series introduce the complexity, asymmetry, and nonlinearity in the behaviour of market participants [20, 34, 36, 38, 39]. Empirically, one sure way of catering for nonlinearity and asymmetry is through decomposition, which delineates observations into intrinsic time representing the short-, medium-, and long-term horizons. Consequently, in measuring the flow of information between commodity and stock markets, the right techniques need to be employed.

To cater for noise in the data series that may compromise the quantification of information transfer, we employ the ensemble empirical mode decomposition (EEMD) approach to demarcate observations into their inherent mode functions (IMFs), which are cyclicities that corroborate investment horizons [40]. The EEMD performs better and overcomes the limitations of approaches such as the Fourier and wavelet transforms and the empirical mode decomposition (EMD) [9]. In terms of transfer entropy, we employ the Rényi entropy (RE), which is a unique form of entropy capable of applying deserving weights to distinct tails of a given data series. The heavy tails contained in financial data sets are unaccounted for by the Shannon entropy [8, 9, 20, 24, 25]. Thus, the RE is appropriate.

We offer several contributions to the body of knowledge. First, we use the five essential FAO food commodity indices, which are rarely studied together in previous works. The use of the world food index and its constituents gives a broad spectrum for analysis as opposed to earlier works that focus on a few commodities or commodity classes like energy or agriculture [12, 41, 42]. The FAO and the UNECA have cautioned against persistent volatilities in food commodities in the past few months, and these volatilities, according to UNECA [6], are forecasted to remain in the uncertain periods of the COVID-19 pandemic. Thus, we contribute by examining the situated information flow between the returns on food commodity indices and regional and global stock indices, given that stock markets have also been volatile in recent periods [8]. It then becomes essential to analyse the diversification hedge and safe-haven potentials as well as policy implications across diverse time scales. Second, frequency decompositions provide a procedure for examining, at various time scales, how commodity and stock indices observe each other through mutually shared information. Through the frequency-domain analysis, economic agents and policy-makers modify, adjust, and adapt to policy actions conditioned on investment horizons.

Third, our study significantly differs from the recent extant studies that are largely limited around specific class(es) of commodity and/or stock markets. The extant literature contains works that focus on energy commodities [56, 60], the US or selected stock markets [42–44], or realised volatilities [59], etc. Whilst these works do not capture food commodities or fail to extend their sample period to the prevailing systemic risk, the quantification of the mutual information shared is completely missing in the case of world food indices. The dynamics between world food commodity markets are necessary to offer comprehensive insights on portfolio management across regional and/or market blocs. To contribute to the body of knowledge, this gap is abridged by this study through the analysis of the situated information between world food commodity and regional equity markets across the systemic risk of the COVID-19 era.

Fourth, with the stipulated indices, we employ a novel methodology, the EEMD-based transfer entropy, which is yet to be used in tandem with the studied variables. No existing study employs the selected FAO food indices together with regional and global stock indices and uses the Rényi transfer entropy approach. This is an addition to the empirical literature.

Furthermore, fat tails in financial time series, which are particularly powerful in exuberant trading periods, must be accounted for. Our data set covers essential turbulent trading scenarios such as Brexit, the trade tension between the USA and China, and the COVID-19 pandemic. These market stress periods render financial time series even more complex, nonlinear, and asymmetric [9, 25]. Consequently, the transfer entropy, as we employ in this study, offers a novel approach for quantifying causal effects that captures model-free information flow measurement, does not rely on the structure of the data or assumptions about linearity, and overcomes spurious linkages, making it a novel technique for basic causality paradigms such as the Granger causality test [46]. Thus, we examine the dynamic connectedness over the short-, intermediate-, and long-term horizons through the Rényi transfer entropy (RTE) technique.

Our findings suggest that the diversification potentials of cereals and dairy lie in the long term. For food, meat, and vegetable oil, the short- and long-term dynamics resulting from information flow produce diversification benefits for regional and/or global equity markets, whereas sugar provides diversification benefits across all investment scales.

The remainder of this study is structured as follows: Section 2 is dedicated to literature review; Section 3 discusses methods; Section 4 analyses the data and preliminary analysis; Section 5 presents empirical results and discussion; and Section 6 concludes the study.

2. Literature Review

In line with the broad literature on commodity markets, we present our review under the major strands of works in the extant literature as follows.

2.1. Return and Volatility Spillover Dynamics for Agricultural Commodities. The extant literature on food commodities has taken several directions with a new emerging strand that measures the intrinsic information flow between commodities. From the family of GARCH, earlier works focused on the volatility transmission between commodities.

Over the period 2003–2010, Lahiani et al. [47] investigate the return and volatility spillovers for four key agricultural commodities—sugar, wheat, maize, and cotton—using the VAR-GARCH. Their findings demonstrate that agricultural commodity returns and volatilities have significant volatility spillover links. When the GARCH models were employed on daily prices of eight main commodities (including crude oil, gasoline, barley, heating oil, maize, sorghum, and wheat), Mensi et al. [48] investigate the dynamic return and volatility spillovers between globally traded energy and cereal commodity markets and the effects of three different forms of OPEC news announcements on volatility spillovers and market persistence. Their findings divulge strong ties between the energy and grain sectors. Additionally, Mensi et al. reveal that OPEC news releases have an impact on the oil markets as well as the oil-cereal connection. The authors show that after accounting for OPEC announcements in these multivariate GARCH models, volatility persistence diminishes (increases) for crude oil and heating (gasoline) returns but mixed outcomes for the cereal markets.

Baldi et al. [49] study commodity financialisation and the progressive integration of commodity and financial markets and the extent to which stock market shocks affect commodity price volatility. The authors report that during the 2008 financial crisis, volatility spillover grew dramatically, indicating a growing interconnectedness between financial and agricultural commodity markets. Through the ARMA-GARCH model, Shahzad et al. [50] analyse how much oil impacts the pricing patterns of agricultural commodities including wheat, maize, soybeans, and rice under bearish and bullish market states. The authors find evidence of symmetry in the tail dependency between the studied commodities and asymmetry in the oil-to-agricultural-commodity spillovers, which become more intense during the financial crisis.

The price dynamics of a variety of worldwide staple foods and cash crop futures prices are investigated by Amrouk et al. [51] using a multivariate Copula-DCC-GARCH model and a rolling-sample volatility index to determine the direction of the volatility spillover for staple-cash commodity couples. The authors report that the strength of interaction fluctuates significantly over time but is typically positive and greater during the period 2007–2012, when commodity prices were high and financial markets were stressed. Śmiech et al. [12] examine the causes of food price volatility between corn, soybean, wheat, rice, US currency, crude oil, and SP500 futures with daily series data from January 4, 2000, to April 1, 2017. The authors use the generalised vector autoregressive framework in a rolling sample method and report that volatility spillovers change over time.

A new strand of literature that utilises methodologies from the family of wavelets was initiated. Živkov et al. [37] examine the multiscale dynamic interconnectedness between wheat, maize, soybean, oats, and rice, using the wavelet methodology. The authors reveal that shorter (longer) time horizons have low (strong) coherence regions, providing evidence in support of the concept of diversity. In the time-frequency domain, Tiwari et al. [52] examine the lead-lag connection between energy fuel price indices and food, industrial inputs, agriculture raw materials, metals, and drinks through the wavelet methodology with a data set spanning between 1990 and 2017. The wavelet coherency results show that the fuel and food prices, the fuel and industrial prices, and the fuel and metal prices all have major and significant relationships. With monthly data from 1997M1 to 2019M12, Frimpong et al. [3] use the wavelet techniques to explore the time-frequency influence of global EPU on the linkages between oat, rice, maize, wheat, and soybean. The authors reveal variation in linkage patterns of the agricultural commodities market at different scales of time and frequency, which is particularly pronounced at low scales.

2.2. Commodity Markets, Information Flow, and Systemic Risks. The recent strand of literature encompasses studies that examine the information flow between commodities. Using the transfer entropy approach, da Silva et al. [53] investigate the path of information flow between Brazilian ethanol and sugar prices and global crude oil prices. For the return and volatility series, da Silva et al. found stronger information transfer from crude oil to sugar and crude oil to ethanol, but for the original series, the net information transfer was in the reverse direction. Caglar and Hancock [54] look at how to infer networks containing time series data and how to characterise information flow across time series using two distinct information-theoretic methods. The first employs Jensen-Shannon divergence to quantify network similarity and uses transfer entropy to characterise information flow. The second method compares the distribution of correlations across edges for different networks using time series correlation and Kullback–Leibler divergence.

Huynh [46] takes a look at the causal link between precious metals prices and uncertainty, as assessed by the two proxies: Economic Policy Uncertainty (EPU) and the Chicago Board Options Exchange Volatility Index (CBOE-VIX). Huynh evaluates data for gold, silver, palladium, and

platinum using two cutting-edge methodologies: multilayer perceptron neural network nonlinear Granger causality and transfer entropy. The author finds that gold remains the most popular safe-haven asset for hedging against risk. The studied precious metals were also shown to influence EPU and VIX, although they are resistant (unresistant) to EPU (VIX) shocks.

Huynh's study not only adds to a growing body of literature by introducing new quantitative methodologies reinforced by neural networks and econophysics but also sheds light on shock transmission mechanisms in commodity markets. A new strand of literature focusing on transfer entropies [55, 56] emerges in the body of knowledge. Under the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) paradigm, Niu and Hu [55] combined the transfer entropy from information theory with the multiscale analysis to measure the information transfer between the Chinese stock market and commodity futures. The authors find heterogeneous interrelations between the stock markets and the agricultural commodity futures, energy, and metals markets. Liu et al. [55] investigate international commodity price interactions from the standpoint of information transmission through a transfer entropy network hinged on empirical mode decomposition. At various time scales, the authors show that as time passes, the network transmission structure and core varieties alter. The authors find metals (energy) to have the highest transmission intensity in the near (medium- and long-run) term(s).

Through an asymmetric methodical framework, Rehman et al. [57] investigate the portfolio prospects and implications for energy and nonenergy assets with data in weekly frequency from 2010M1 to 2018M6. The long-run effect of oil price shocks on metal commodities was revealed. Wheat was the only food commodity considered in their study. The dynamics between other food commodity markets are necessary to offer comprehensive insights on portfolio management. The dynamic interrelations between commodity futures (i.e., crude oil and gold) and stock market returns from the USA, China, Germany, France, and Japan were analysed by Mezghani et al. [58] under the BEKK-GARCH and the Diebold–Yilmaz spillover connectedness frameworks. Their study was limited to gold and oil, with no evidence of how the returns from the studied stock markets comove with the returns from global food commodities.

Among strategic commodities and the US stock markets, Bouri et al. [43] examine the spillover dynamics with data spanning from April 11, 2006, to April 29, 2019. Whilst the significance of this study cannot be overlooked, the period does not cover the systemic risk era of COVID-19. Besides, these dynamics were not investigated for food commodity markets. Between national stocks and global commodity prices, Enilov et al. [44] examine their linkages with a mixed-frequency vector autoregression approach with weekly and monthly data sets covering the period 1951M1 and 2018M3. Aside from not covering the COVID-19 era, the peculiarities between stock markets and global food commodity indices were not considered by their study.

With the dependence parameter copula, Karakaş et al. [45] examine the vine copula interdependence structure of commodity and stock markets, limiting their scope to stock markets of the USA, Turkey, and the UK, and the only food commodity considered was soybean, whilst the study period (2017–2019) fails to incorporate an essential systemic crisis period, the COVID-19 pandemic. Recent works that forecast volatility dynamics between commodities provide no insights on global food commodities (see, e.g., [59]). As Iqbal et al. [60] incorporate agricultural commodity futures in their modelling of tailed risk dependence of commodity markets, it paves way for assessments of the intrinsic information content that is mutual to various commodity markets. As we find that the existing studies either do not capture food commodities or fail to extend their sample period to the prevailing systemic risk, this study seeks to overcome the empirical gap in the area of food commodity and regional stock markets by assessing the situated information flow common to global food commodity and regional stock market returns using the transfer approach, which was recently used in the context of energy markets by Ferreira et al. [61].

2.3. Motivation. From the extant literature, thus far, empirical evidence on the intensity and flow of intrinsic information flows food commodities is lacking. Frimpong et al. [3] documented that sudden shifts in policy uncertainty have a propensity to affect commodity price comovement, which puts the agricultural commodities market's stability in danger, necessitating policymaker involvement to prevent a spillover risk contagion effect in uncertain times. At this time when food price volatilities are intense and projected to continue in the period of the COVID-19 pandemic [4, 6], an assessment of the intrinsic information flow—situated on mutual policy actions and uncertainties—between food commodities is essential to influence effective policymaking and portfolio risk management. Furthermore, as documented by Shahzad et al. [50], increases in agricultural commodity prices have the potential to affect not just social and economic costs but also education, family, and health relationships owing to economic policy actions and uncertainties [3].

Therefore, to complement the emerging strand of works in the literature, we employ the transfer entropy technique hinged on decomposed data series to estimate the frequency-domain information flow between global food commodity markets. Our study is linked with the work of Hanif et al. [15] study in terms of the studied commodity indices. Hanif et al. consider the nonlinear relationship dynamics and risk spillovers between oil prices and global food prices, proxied by the world food price index and its subcategories: dairy, cereals, vegetable oil, and sugar. Employing the same set of food commodity indices together with regional equity markets, we add to the extant literature by quantifying the intrinsic information between these assets in the frequency space, which caters for nonlinearity, asymmetry, and heterogeneity of market participants, to assess the diversification benefits for portfolios containing these food

commodities amid their rapid financialisation in recent decades [10, 11].

The heterogeneous markets hypothesis of Müller et al. [62] suggests that market participants make investment decisions across distinct time (investment) scales after adjusting their risk/reward preferences. Therefore, considering the persistent volatilities in the FAO commodity prices and the consequences of excessive capital injections towards commodity financialisation [63–66], we maintain that this study is timely.

3. Methods

Our methodical approach is in two steps. In the first, we use EEMD to extract intrinsic mode functions (IMFs) from the food commodity and stock returns, and in the second, we estimate transfer entropies with the IMFs as inputs. Given the nonlinearity and nonstationarity within and among our time series variables, IMFs are essential in this research since they reflect various time scales of the original time series [67]. In the context of commodity markets, recent works (see, e.g., [43, 57, 59, 60]) have also underscored nonlinearity and asymmetries in their cross-market linkages and spillovers. This means that analysing the information transfer between the sampled markets across various scales is essential.

3.1. Ensemble Empirical Mode Decomposition (EEMD). An advanced version of the EMD-induced signal processing approach is provided by the EEMD, which corrects for the effect of mode-mixing associated with the EMD. We carefully follow Wu and Huang's [68] procedures to summarise the EEMD algorithm as follows.

Generally, $y(t)$ is the aggregate of the actual data known as the signal $\alpha(t)$ and noise $(n(t))$, so that

$$y(t) = \alpha(t) + n(t). \tag{1}$$

Next, we generate from equation (1), i^{th} as a calculated observation, $y_i(t)$, in equation (2), by appending a white noise of various realizations, $\omega_i(t)$, which eradicates mode mixing and yields a consistently sound reference scale distribution to facilitate empirical mode decomposition.

$$y_i(t) = y(t) + \omega_i(t). \tag{2}$$

Thus, following Huang et al. [40], we generate the EEMD in four specific summarised stages:

Stage 1. Get $y_i(t)$ through the addition of white noise to the main data

Stage 2. $y_i(t)$ is decomposed into its inherent functions

Stage 3. The outputs from the first two stages are iterated with fluctuating series of white noise

Stage 4. The ensemble averages of linked IMFs of the decomposition are finally generated

The "libeemd" package of Luukko, Helske, and Räsänen [69] from R programming is used for these processes to develop the EEMD for this study.

3.2. Rényi Transfer Entropy. Transfer entropy is a consequence of Hartley's [70] general information theory. The quota of possible symbolic series in a given probability distribution is used to compute the quota of possible symbolic series in a given probability distribution [71, 72]. As an uncertainty measure, modern studies on TE employ Shannon's [73] arithmetical communication theory, which is gleaned from theoretic information.

The average symbolic information for a probability distribution having distinguishable symbols of a particular experiment P_j is expressed as follows:

$$H = \sum_{j=1}^{n} P_j \log_2\left(\frac{1}{P_j}\right) \text{bits}, \tag{3}$$

where n is the quantity of differing symbols associated with probability p_j [70]. The average number of bits necessary for optimal encoding autonomous draws may be estimated with Shannon's [73] paradigm (i.e., Shannon entropy (SE)) for a discretised random variable J with $p(j)$ probabilities.

$$H_J = -\sum_{j=1}^{n} p(j)\log_2 p(j). \tag{4}$$

Given two Markov time series procedures, a quantification of information flow between them is made with Kullback and Leibler's [74] distance model (KLDM). Let I, with marginal probability $p(i)$, and J with marginal probability $p\ (j)$ represent two discrete random time series. Their joint probability is then defined as $p(i, j)$. At order k (process I) and I (process J), we also assume dynamic stationarity for the Markov process. As stated by the Markov property, the probability at which I is observed in state i and time $t+1$ conditioned on k preceding data points is $p(i_{t+1}|i_t, \ldots, i_{t-k+1}) = p(i_{t+1}|i_t, \ldots, i_{t-k})$. The mean bits needed for encoding the data point at $t+1$ prior to knowing k observations are given as follows:

$$h_j(k) = -\sum_i p\left(i_{t+1}, i_t^{(k)}\right)\log_2 p\left(i_{t+1}|i_t^{(k)}\right), \tag{5}$$

where $i_t^{(k)} = (i_t, \ldots, i_{t-k+1})$ (correspondingly for process J). Information flow to I from J is examined in a bivariate case by quantifying the variance from the Markov property $p(i_{t+1}|i_t^{(k)}) = p(i_{t+1}|i_t^{(k)}, j_t^{(I)})$, as hinged on the KLDM. SE is then expressed as follows:

$$T_{J\longrightarrow I}(k,l) = \sum P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log\frac{P\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}{P\left(i_{t+1}|i_t^{(k)}\right)}, \tag{6}$$

where $T_{J\longrightarrow I}$ aggregates the information flow towards I from J. Analogously, the flow of information to J from I, which is $T_{J\longrightarrow I}$, can be obtained. The net estimate of information flow is computed as the excess of $T_{J\longrightarrow I}$ over $T_{J\longrightarrow I}$, which serves as the central information flow path.

The expediency of SE in the area of finance cannot be overemphasised, but it does not attribute equal weights to all probable expectations in a probability distribution. Note that fat tails are pervasive in asset pricing, but SE does not overcome this assumption. Therefore, we resort to Rényi's [75] transfer entropy, which uses a weighting value q, to overcome the shortfall of SE. RTE is computed as follows:

$$H_J^q = \frac{1}{1-q}\log_2 \sum_j P^q(j), \tag{7}$$

with $q > 0$. For $q \longrightarrow 1$, RE and SE converge. For $0 < q < 1$, more weight is assigned to low probability events, while for $q > 1$, outputs j with higher initial probabilities are favoured by the weights. Resultantly, based on q, RTE facilitates the assignment of different weights to unequal regions of the distribution [20, 25, 71]. This feature of RTE makes it superior over SE and, hence, its desirability in finance.

The companion distribution $\varnothing_q(j) = (p^q(j)/\sum_j p^q(j))$ for $q > 0$ is applied to normalise the weighted distributions [76], from which RE is estimated as follows:

$$RT_{J\longrightarrow I}(k,l) = \frac{1}{1-q} p\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log_2 \frac{\sum_i \varnothing_q\left(i_t^{(k)}\right) P^q\left(i_{t+1}|i_t^{(k)}\right)}{\sum_{i,j} \varnothing_q\left(i_t^{(k)}, j_t^{(I)}\right) P^q\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}. \tag{8}$$

Note that negative estimates could be provided by the RTE. Noting the history of J, in this case, suggests significantly extra uncertainty than noting the history of I only would imply. Negative (positive) estimates depict higher (lower) risks in this context.

TE estimations are subject to biases in small samples [77]. The effective transfer entropy (i.e., ETE) can resolve this and is derived as follows:

$$ETE_{J\longrightarrow I}(k,l) = T_{J\longrightarrow I}(k,l) - T_{J\,\text{shuffled}\longrightarrow I}(k,l), \tag{9}$$

where the TE using faltered forms of the data series J is represented as $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$. The procedure removes the data series' serial reliance of J, whilst the statistical linkages amid J and I are preserved through repetitive random draws from the given return series J and rearranging them to produce a fresh return series. $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$ is therefore caused to approach zero as the sample size increases; nonzero values of $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$ are caused as a result of biases with a small sample. Consequently, recurrent shuffles and the average of the shuffled TE estimates across all replications could be employed as an estimator of few sample biases, from which the derivation of bias-corrected ETE estimates is gotten after being deducted from the RE or SE estimates.

To establish the statistical significance of ETEs, the Markov block bootstrap technique is adopted. This process retains the dependencies within the variables J and I but eliminates their statistical linkages as opposed to shuffling. Resultantly, in line with the H_0 of "no information flow," a distribution of TE estimates is retrieved by bootstrapping. $1 - \widehat{q}\mathrm{T}$ provides the accompanying $p-$value, while $\widehat{q}\mathrm{T}$ offers a specification of the quantile of the simulated distribution produced by the relevant TE estimations (see [8, 71]).

4. Data and Preliminary Analysis

Our data set includes monthly indices on the aggregate world food commodity index and its constituents including cereals, dairy, meat, vegetable oil, and sugar and 11 regional NASDAQ equity indices for Asia, Asia-Pacific, BRIC, developed markets, emerging markets, Europe, Eurozone, global market, Latin America, the Middle East and Africa, and North America. The data set spans from December 2012 to September 2021. The world food commodity indices are provided by FAO and are available in monthly periodicities, and the equity indices are supplied by EquityRT. A trajectory of the commodities and regional equity indices' returns is presented in Figure 2.

At a glance, the return series suggests high volatilities in all indices, with high intensity in 2020/2021. For the studied food commodity indices, we spot drops in returns, with sugar and vegetable oil experiencing the sharpest drop in the COVID-19 era. A similar observation is made for the aggregated indices, the food price index, suggesting that aggregated losses are higher for food commodities in the studied COVID-19 period. For the studied regional equity markets, intense volatile clusters are found in the COVID-19 period with the global market index being an exception. This exception suggests that the aggregated impact of COVID-19 on global indices may not be felt, as extreme negative returns may be offset by extreme positive returns. Notwithstanding, over the studied period, the worse return on the global market index is spotted within 2016, which falls within a key incident, Brexit. The descriptive summary of the studied indices is presented in Table 1.

The descriptive statistics suggest that except for cereals, the returns on all other food commodity indices witnessed a positive mean over the studied period. Sugar and vegetable oil were found to have the highest return deviations, substantiating why the two indices had the sharpest drop in returns. Except for Latin America, all regional equity markets realised positive mean returns over the period. The studied commodity indices (equities) supported (rejected) normality, as indicated by the Normtest.W statistics. These statistics reignite the essence of this study.

5. Empirical Results and Discussion

This section presents and discusses the study's principal objective. The bidirectional intrinsic information flow between food commodities and regional equity markets is examined. The Rényian entropy approach generates both

Table 1: Descriptive summary.

Commodities/equities	Min.	Max.	Mean	SD	Skewness	Kurtosis	Normtest.W
Agricultural commodities							
Food	−0.0458	0.0480	0.0005	0.0200	0.0132	−0.4582	0.9920[(a)]
Meat	−0.0563	0.0471	0.0005	0.0205	−0.2722	−0.1107	0.9915[(a)]
Dairy	−0.0891	0.1055	0.0000	0.0344	−0.0522	0.6144	0.9808[(a)]
Cereals	−0.0734	0.0721	−0.0009	0.0294	0.0839	−0.2119	0.9933[(a)]
Veg. oil	−0.1328	0.1355	0.0034	0.0482	0.0312	0.1012	0.9873[(a)]
Sugar	−0.2125	0.1596	0.0001	0.0628	−0.2362	0.8326	0.9870[(a)]
Equities							
Asia	−0.1202	0.0927	0.0049	0.0366	−0.5413	1.0122	0.9731
ASPA	−0.1370	0.0977	0.0044	0.0378	−0.6146	1.4487	0.9688
BRIC	−0.2109	0.1410	0.0021	0.0518	−0.5932	1.8435	0.9715
Developed markets	−0.1519	0.1225	0.0080	0.0387	−0.6964	2.7251	0.9441
Emerging markets	−0.2146	0.1205	0.0021	0.0468	−0.8090	3.1257	0.9561
Europe	−0.1696	0.1580	0.0036	0.0444	−0.3446	1.9532	0.9670
Eurozone	−0.1958	0.1870	0.0046	0.0501	−0.2644	2.2892	0.9640
Global market	−0.2668	0.1148	0.0059	0.0651	−1.1270	1.8427	0.9285
Latin America	−0.4486	0.1970	−0.0045	0.0813	−1.2941	7.0333	0.9114
Middle East and Africa	−0.2773	0.1125	0.0001	0.0580	−0.9663	3.4944	0.9430
North America	−0.1536	0.1236	0.0104	0.0397	−0.7520	2.8274	0.9395

Notes. This table presents the descriptive statistics of the world food commodity and global equity indices' returns. Panel A presents the descriptive statistics for the world food indices, and Panel B presents the descriptive statistics for the regional equities. Veg. oil – vegetable oil and SD – standard deviation. [(a)] Significance at 1%.

negative and positive effective transfer entropies (ETEs). Negative ETEs represent high risk while positive ETEs indicate low risk. We conduct our analysis from the perspective of portfolio diversification. Among equities, diversification is permitted when negative ETEs recipients are paired with positive ETEs recipients, whereas between commodities and equities, diversification is possible with equities that negatively respond to shocks from (to) commodities (equities). Per the stylised facts of the financial data series, we account for fat tails in the return series by specifying a fault weight of 0.30. We present our results in both the composite and frequency domains. IMFs 1–5 and residual are used in the latter to show intrinsic times corresponding to short-, mid-, and long-term characteristics. The residual embodies the long-term path and reveals the fundamental character of the particular commodity and equity series. Using time scales, we assess one market's (food commodity indices') dynamic reaction to the other (regional equity markets) based on the situated information mutual to the markets.

At the composite (frequency-domain) level, black specks inside red (blue) bars indicate ETEs. The ETEs are depicted in the composite state in Figure 2 and the frequency-domain states in Figures 3–6. The 95% confidence bounds are located at the ends of the red or blue bands. As a result, we must reject the null hypothesis of "no information flow" if these confidence boundaries are in the positive or negative portions. Confidence bounds overlapping at the origin connote insignificant information flow. In Table 2, the ETEs in Figures 3–6 are numerically given.

5.1. Composite ETEs. We analyse the composite ETEs between the returns on world food commodity indices and regional equity markets. The ETE plots in Figure 3 are for cereals, dairy, food, meat, vegetable oil, and sugar. We analyse the ETEs for the various commodity markets in turn.

At the composite level, from Figure 3, we find that when shocks are present in food commodity markets, all regional equity markets respond negatively, but the aggregate response to such shocks is positive, which is evidenced by the positive ETE for the global market index. This observation reiterates the fact that the aggregated impact of COVID-19 on global indices may not be felt, as extreme negative returns may be offset by extreme positive returns. These ETEs, however, are insignificant. Conversely, aside from North American equities that transmit significant negative flow towards cereals, all other ETEs from equities towards cereals are insignificant.

No significant ETEs are found for ETEs towards equities, but equities from Asia, Eurozone, North America, and developed markets transmit positive (low-risk) ETEs towards dairy. For the food price index (FPI), Latin American stocks receive positive ETEs, while all ETEs both from FPI and equities are insignificant. For meat and vegetable oil, no significant ETEs are found. ETEs from sugar to equities were all positive with Global, Asia-Pacific, developed markets, and the Middle East and Africa being significant. Stocks from North America, developed markets, BRIC, and the Middle East and Africa transmit positive flows towards sugar, whereas global stocks transmit a negative flow.

At this point, it is essential to note that at the composite level, the only diversification prospect between equities amid commodity markets is that of global stocks against North America, developed markets, BRIC, and the Middle East and Africa. It is equally important to note that despite being highly risky, negative ETE recipients provide potential diversification to the commodity or equity market in question based on flow towards equity and commodity markets,

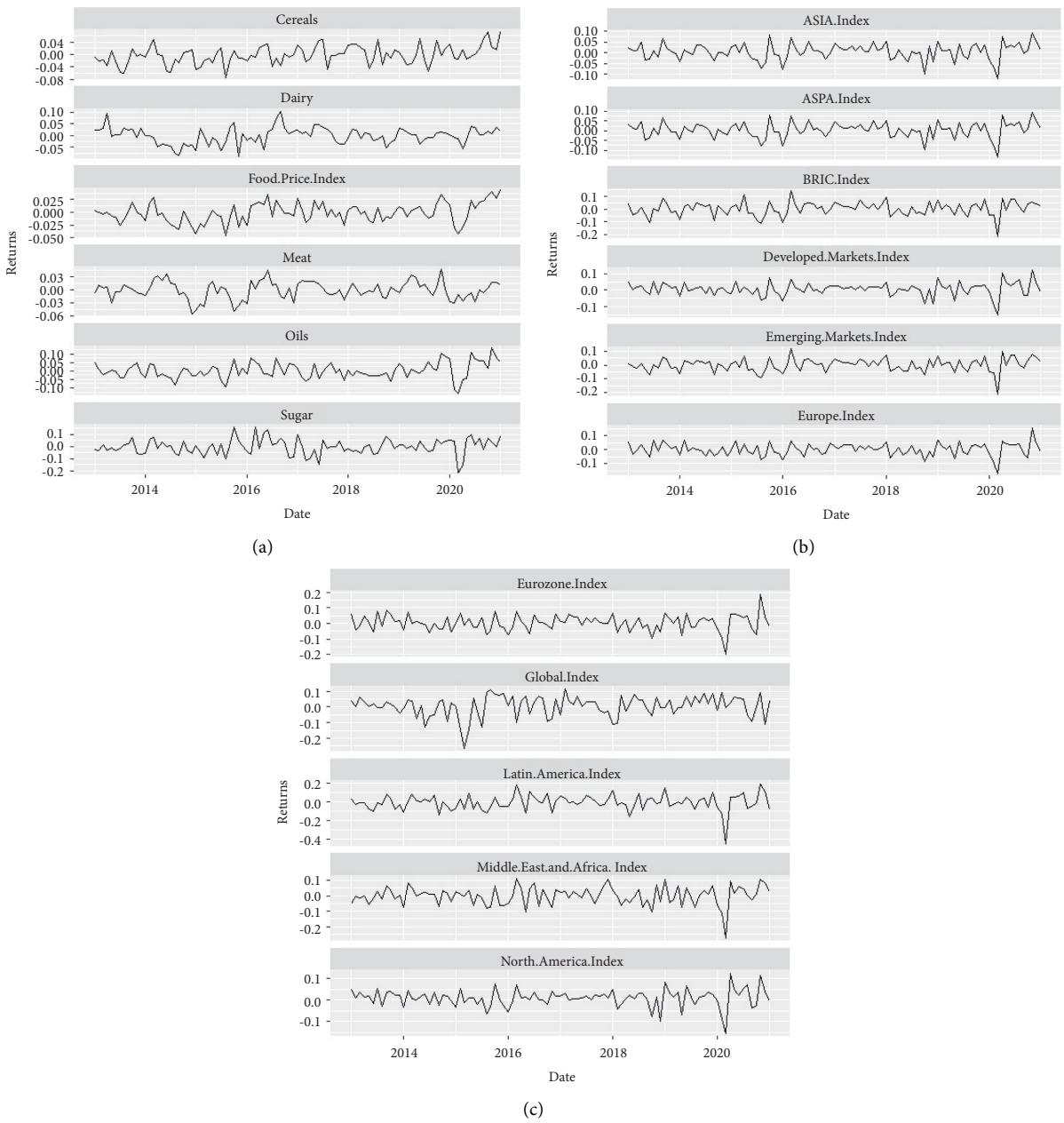


Figure 2: Time series plots of food commodity indices.

respectively. To provide evidence in the frequency domain, which are particularly of interest to short-, medium-, and long-term investors [8, 9], we turn to the frequency-domain ETEs.

5.2. Frequency-Domain ETEs. Just like the behaviour of market participants, commodity markets are noted to be heterogeneous [43, 57, 60, 78, 79]. Besides, given the fat tails embedded in financial time series, it is essential to delineate the return series into time horizons that correspond to investment terms of short-, medium-, and long-term periods. Following existing works [8, 9, 25], we attribute IMF1 and IMF2 to the short term, IMFs 3–5 to the intermediate-term, and IMF Residual to the long term. The short-, medium-, and long-term horizons are defined by Yang et al. [80] to be characterised or driven by investor sentiments and microstructure of the market, the significance of key events, and fundamental dynamics, respectively. We discuss the ETEs following the delineated investment horizons.

In the short term (Figure 4), we find no diversification potential from the ETEs. However, there are significant ETEs that need to be singled out. At IMF1, the global equity market receives (transmits) positive information flow from (to) cereals. Thus, cereals and global stocks are less risky to each other in terms of the mutual information they share. Stocks from Asia (the Middle East and Africa) transmit significant flow to the dairy (food) market. For information

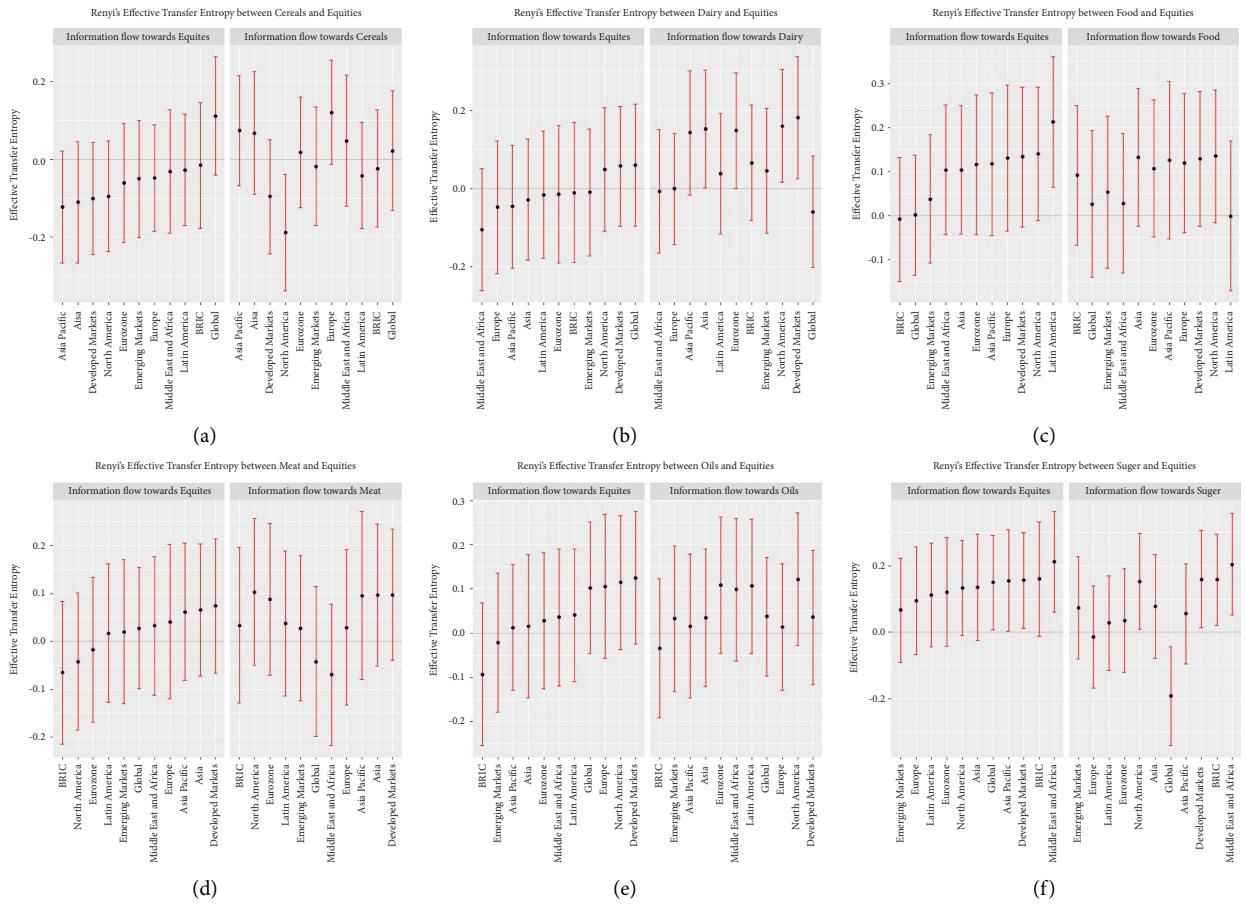


Figure 3: Transfer entropies at the composite level. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets for the signal/composite data. (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities.

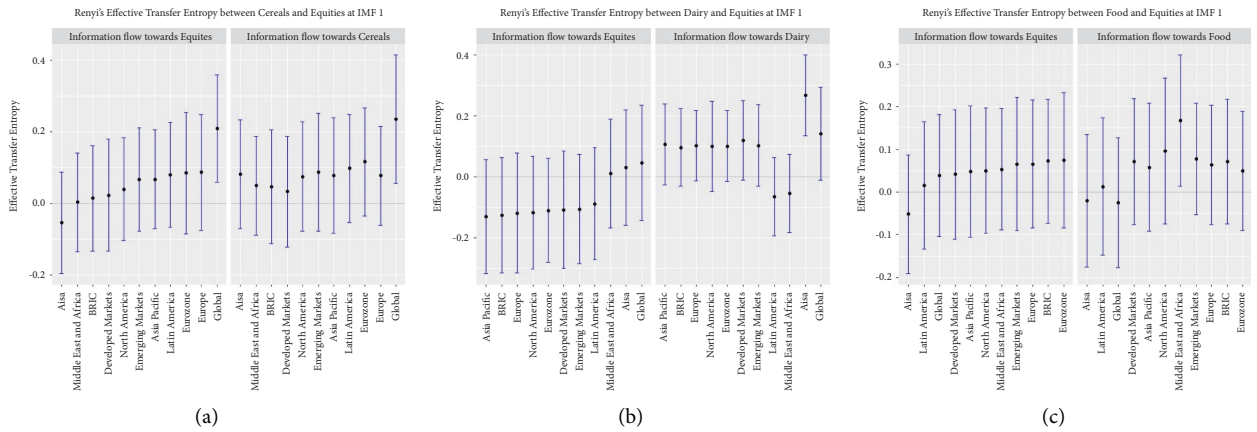


Figure 4: Continued.

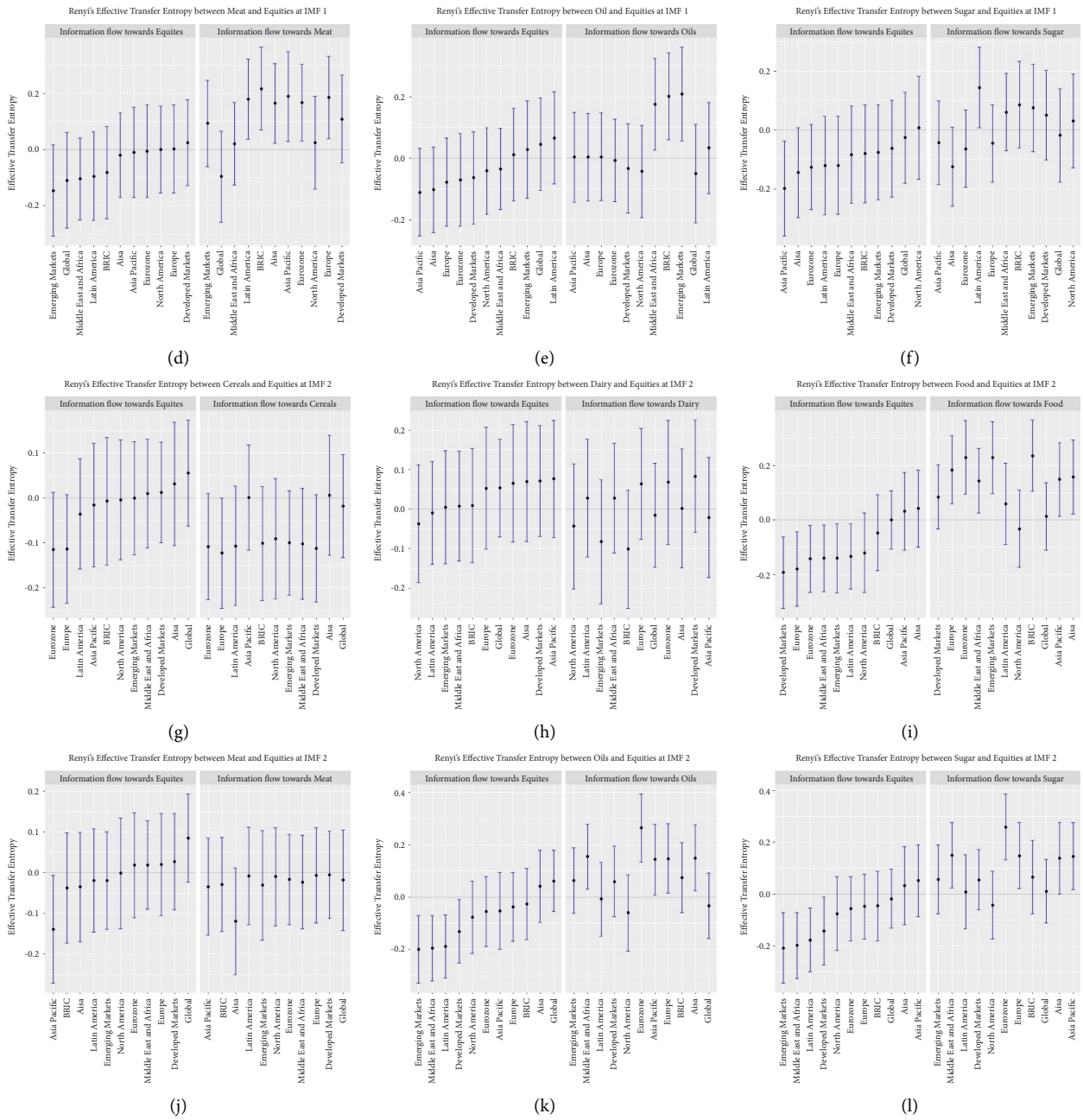


Figure 4: Transfer entropies in the short term. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets at short-term scales (IMFs 1 and 2). (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities for IMF1 with their corresponding IMF2 being (g) to (l).

flow towards vegetable oil, the Middle East and Africa, BRIC, and emerging markets transmit positive ETEs. Sugar transmits a negative information flow to Asia-Pacific stocks, suggesting that when contained in a portfolio, sugar could diversity with Asia-Pacific stocks when they are affected by commodity market shocks, but not vice versa. Latin American equity markets transfer a positive flow towards sugar.

At IMF2, equity of developed markets, European, Eurozone, Middle East and Africa, emerging markets, and Latin America receive negative ETEs from food. Thus, when the food market experience shocks, they are well diversified by the inclusion of stocks from the aforementioned markets. However, no diversification among equities is significant. Except for the equity markets of developed markets, Latin and North America, and Global markets, all other regional equity markets transmit positive information flow towards the food market. Asia-Pacific stocks are negative ETE recipients from the meat market. In both vegetable oil and sugar markets, emerging markets, Middle East and Africa, Latin America, and developed markets are negative ETE recipients, which suggests their potential as possible

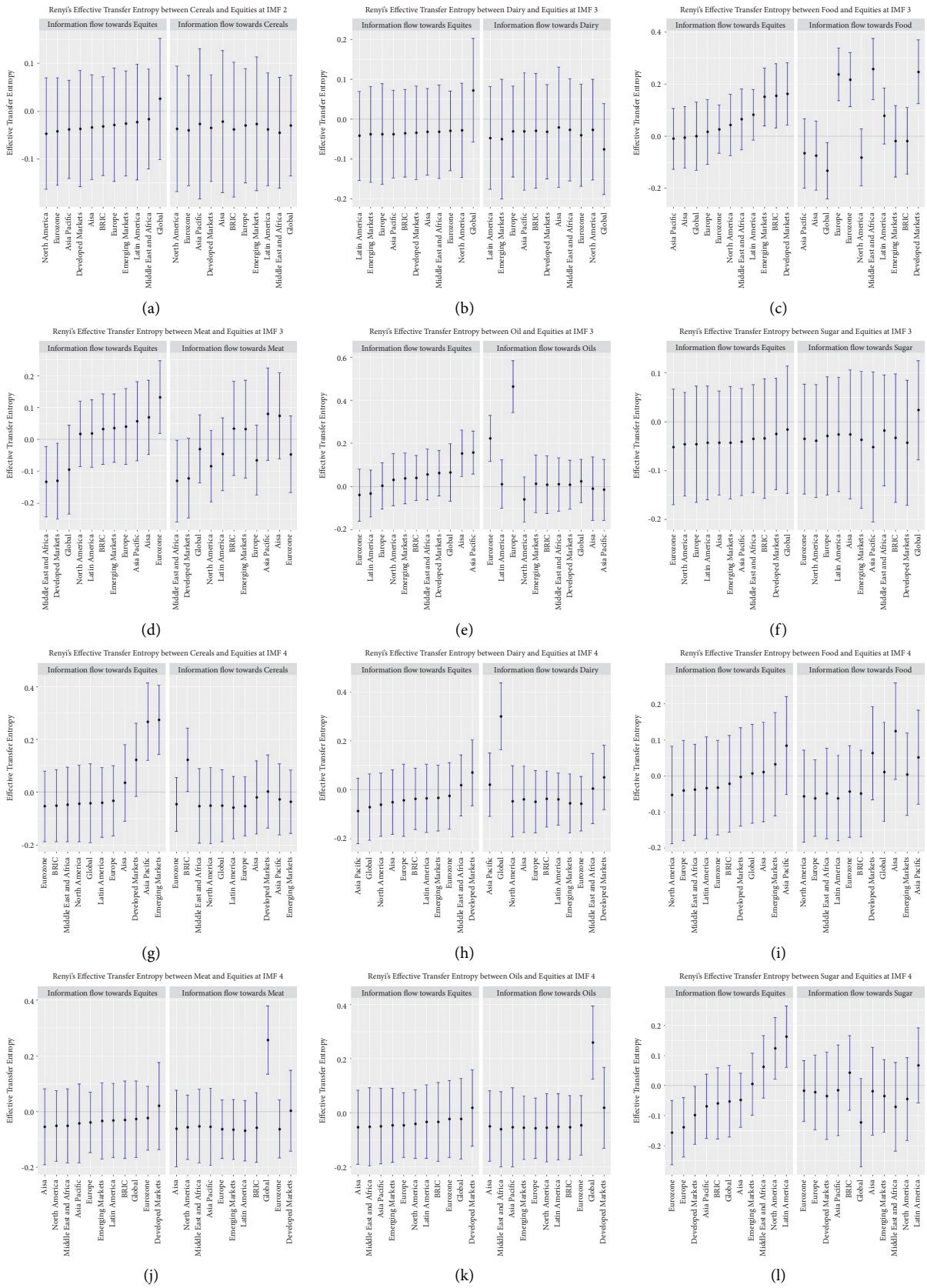


Figure 5: Continued.

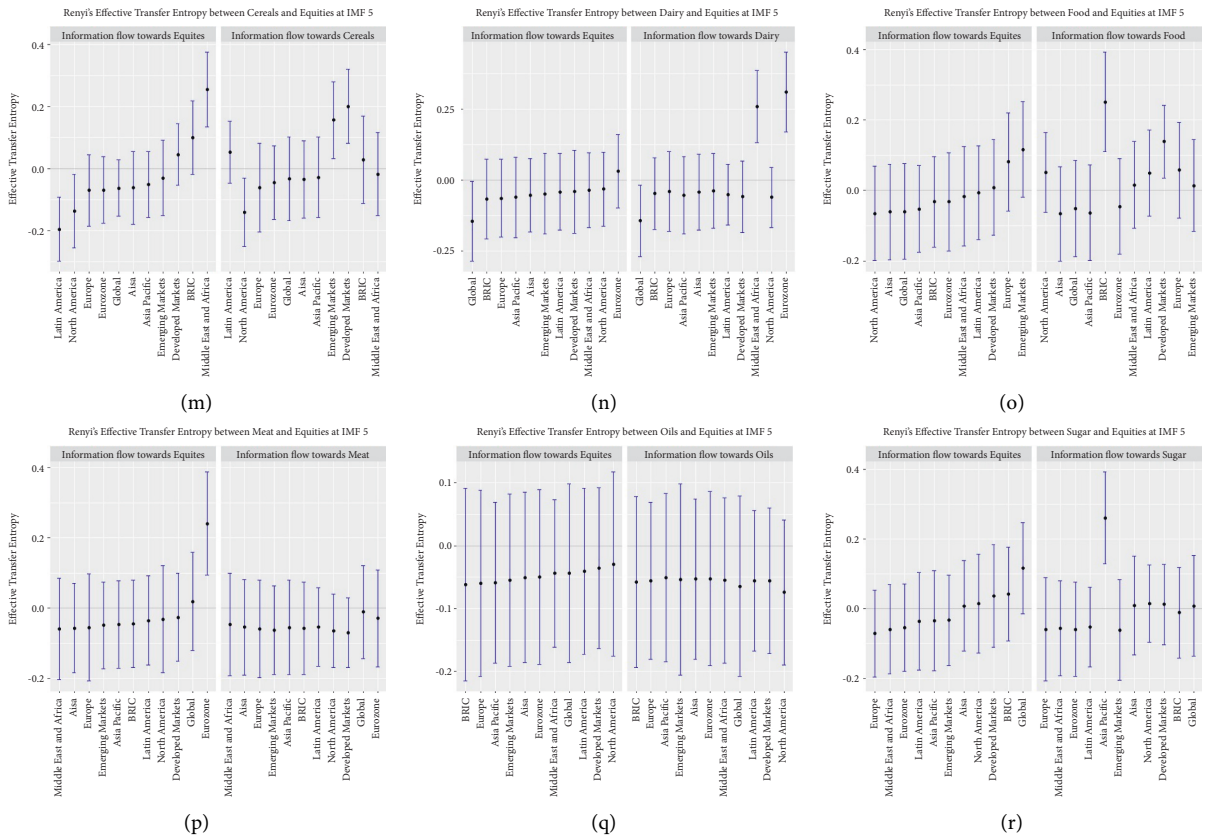
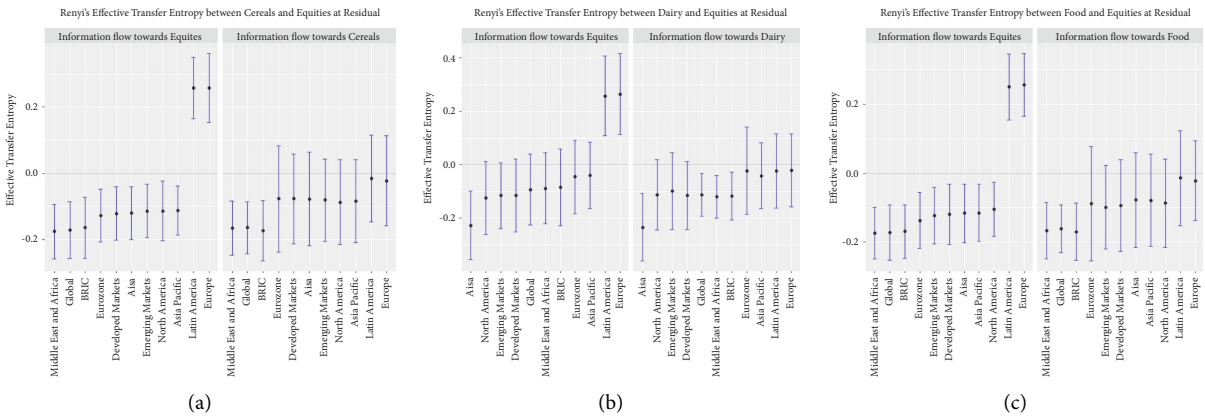


Figure 5: Transfer entropies in the mid-term. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets at medium-term scales (IMFs 3–5). (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities for IMF3 with their corresponding IMF4 and IMF5 being (g) to (l) and (m) to (r).



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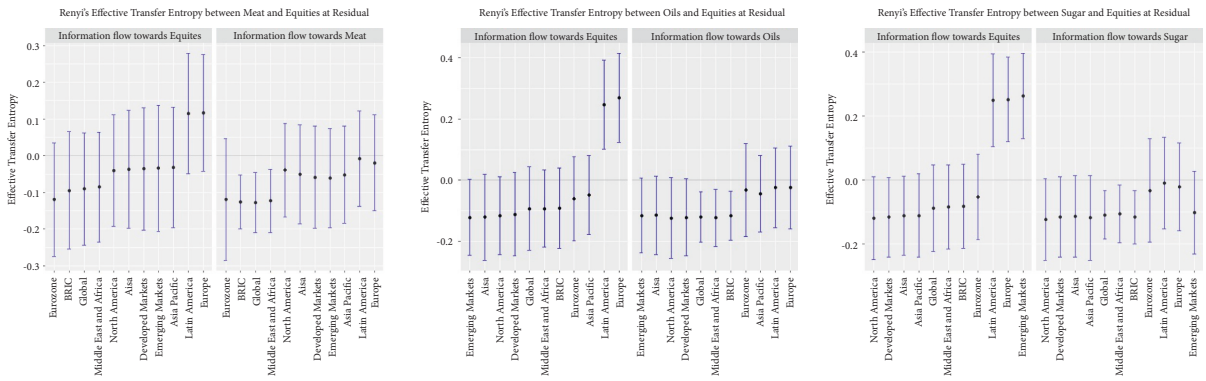

(d) (e) (f)

Figure 6: Transfer entropies in the long-term. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets at the long-term scale (residual IMF). (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities.

diversifiers to vegetable oil. The significant positive ETE transmitters to vegetable oil include the Middle East and Africa, Eurozone, Asia-Pacific, Europe, and Asia.

Findings in the short term suggest little diversification chances. This could be attributed to the nature and degree of connectedness between agricultural commodities as espoused by Frimpong et al. [3]. In their study, they report high connectedness between agricultural commodities at high frequencies (i.e., in the short term). These findings further support the works of Živkov et al. [37] and Tiwari et al. [52] who find high linkages between agricultural commodities at short-term scales using multiscale analysis. High connectivity between commodity markets may render diversification futile, and hence, it follows the intuition that the majority of the food commodity classes fail to offer diversification benefits in the short-term frequencies.

Turning to the intermediate term (Figure 5), no diversification potential is found for cereals and dairy markets. Emerging markets, BRIC, and developed markets receive negative ETEs from food at IMF3. Global equities transmit negative flow towards food, making them diversifiable pairs. Additionally, between equities, diversifiable pairs are found for global markets against Europe, Eurozone, Middle East and Africa, and developed markets, when shocks befall equity markets. For meat, negative ETEs are transmitted to the stocks of the Middle East and Africa and developed markets, making them diversification candidates, but on the other hand, only stocks from the Middle East and Africa can diversify with meat. Between equities, when shocks befall the meat market, the Middle East and Africa and developed stocks could diversify with those from Eurozone. With more positive and fewer negative ETEs, this implies that there exist both high- and low-risk transfer entropies. Impliedly, the high-risk ETEs could be offset by their low-risk counterparts. Specifically, with the flow towards equities, the high-risk attributes of investments in equities from the Middle East and Africa and developed markets could be offset by the low-risk attributes of investments from Eurozone markets. In this case, investment in the Middle East and Africa and developed markets' equities pose less risk when the history of other equity markets is known. Stocks from Asia and the Asia-Pacific (Eurozone and Europe) are positive ETE recipients (transmitters) for vegetable oil, leaving out no diversification prospects. It is worthily noting that the varying ETE directions and significance that result in diversification potentials partly communicate the asymmetries in cross-asset connectedness [43, 57, 59, 60].

At IMF4, the Asia-Pacific and emerging markets (BRIC) receive (transmits) positive information flow from (towards) cereals. Global stocks transmit positive flow towards the dairy, meat, and vegetable oil markets. Diversification prospects are available for sugar when it experiences shocks. Sugar could diversify with Eurozone, Europe, and developed markets equities, whereas between equities, the significant diversification pairs are for Latin and North America versus Eurozone, Europe, and developed markets. In the medium term, diversification prospects keep diminishing across IMFs. When shocks are present in the cereals market, stocks from Latin and North America could diversify with cereals, whereas, between equities, the Middle East and Africa could diversify with Latin and North America. On the other hand, with shocks to equity markets, cereals could diversify with North American equities, and between equities, North America versus emerging and developed markets form the significant pairs.

Global equities could diversify with diary for all conditions, whereas, between equities, global markets versus the Middle East and Africa and Eurozone markets serve as the significant pairs when equities experience shocks. BRIC and developed markets transmit positive ETEs towards food, whereas meat transmits a positive ETE to Eurozone equities, leaving no diversification opportunity for either meat or food markets. Except for Asia-Pacific stocks that transmit a positive information flow to sugar, no significant ETEs or diversification prospects are available to the vegetable oil and sugar markets.

A significant observation in the medium term is that the diversification potentials of all commodities diminish with increasing frequencies. The main implication of this result is that when markets observe the behaviour of each other for

Table 2: Transfer entropies between world food commodities and regional equity markets.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Cereals																					
Cereals -> Asia	−0.110	0.095	−1.158	−0.055	0.087	−0.633	0.032	0.083	0.379	−0.033	0.066	−0.504	0.035	0.088	0.397	−0.063	0.071	−0.876	−0.121[b]	0.048	−2.502
Asia -> cereals	0.068	0.096	0.708	0.081	0.093	0.873	0.006	0.081	0.069	−0.021	0.090	−0.238	−0.020	0.084	−0.234	−0.034	0.076	−0.451	−0.078	0.086	−0.912
Cereals -> Asia.Pfc	−0.123	0.088	−1.394	0.067	0.084	0.796	−0.016	0.084	−0.190	−0.038	0.063	−0.605	0.268	0.089	3.005	−0.052	0.065	−0.801	−0.113[b]	0.045	−2.489
Asia.Pfc -> cereals	0.074	0.086	0.858	0.077	0.098	0.788	0.000	0.071	0.007	−0.027	0.095	−0.278	−0.027	0.082	−0.323	−0.029	0.079	−0.360	−0.084	0.076	−1.106
Cereals -> BRIC	−0.015	0.098	−0.153	0.014	0.090	0.151	−0.007	0.086	−0.079	−0.031	0.063	−0.500	−0.051	0.083	−0.612	0.100	0.072	1.377	−0.165[a]	0.056	−2.944
BRIC -> cereals	−0.023	0.091	−0.254	0.046	0.097	0.477	−0.101	0.077	−1.315	−0.038	0.085	−0.449	0.122[c]	0.073	1.675	0.028	0.086	0.324	−0.174[a]	0.055	−3.150
Cereals -> Dev.Mkt	−0.100	0.088	−1.137	0.022	0.095	0.235	0.012	0.068	0.179	−0.036	0.074	−0.492	0.122	0.084	1.456	0.045	0.060	0.756	−0.122[b]	0.049	−2.479
Dev.Mkt -> cereals	−0.096	0.090	−1.067	0.033	0.094	0.347	−0.112	0.073	−1.541	−0.035	0.068	−0.519	0.002	0.084	0.024	0.200[a]	0.073	2.748	−0.078	0.083	−0.940
Cereals -> Emg	−0.050	0.092	−0.543	0.066	0.088	0.750	0.000	0.077	0.003	−0.025	0.067	−0.381	0.274	0.080	3.438	−0.030	0.074	−0.411	−0.114[b]	0.049	−2.328
Emg -> cereals	−0.018	0.093	−0.191	0.086	0.100	0.860	−0.100	0.071	−1.413	−0.026	0.085	−0.309	−0.036	0.073	−0.489	0.156[b]	0.075	2.080	−0.081	0.076	−1.071
Cereals -> Eur	−0.047	0.084	−0.567	0.087	0.099	0.879	−0.114	0.073	−1.549	−0.028	0.072	−0.394	−0.032	0.081	−0.398	−0.071	0.070	−1.012	0.257	0.063	4.055
Eur -> cereals	0.121	0.082	1.482	0.077	0.084	0.921	−0.123[c]	0.075	−1.647	−0.030	0.072	−0.417	−0.053	0.068	−0.779	−0.061	0.087	−0.701	−0.023	0.083	−0.278
Cereals -> EurZ	−0.061	0.094	−0.649	0.084	0.103	0.820	−0.115	0.078	−1.485	−0.042	0.068	−0.620	−0.053	0.082	−0.650	−0.069	0.065	−1.066	−0.129[a]	0.048	−2.655
EurZ -> cereals	0.018	0.087	0.213	0.115	0.092	1.251	−0.109	0.072	−1.513	−0.040	0.070	−0.575	−0.046	0.062	−0.742	−0.045	0.072	−0.628	−0.078	0.097	−0.798
Cereals -> global market	0.112	0.093	1.209	0.209[b]	0.091	2.294	0.056	0.072	0.774	0.026	0.077	0.335	−0.042	0.091	−0.465	−0.063	0.055	−1.139	−0.172[a]	0.052	−3.313
Global market -> cereals	0.023	0.094	0.241	0.235	0.109	2.160	−0.018	0.070	−0.261	−0.030	0.064	−0.474	−0.051	0.083	−0.616	−0.033	0.082	−0.402	−0.165[a]	0.048	−3.445
Cereals -> Lat.Am	−0.027	0.087	−0.309	0.079	0.089	0.886	−0.035	0.075	−0.474	−0.023	0.073	−0.308	−0.039	0.081	−0.486	−0.195[a]	0.063	−3.111	0.256[a]	0.057	4.535
Lat.Am -> cereals	−0.041	0.082	−0.500	0.097	0.091	1.058	−0.107	0.081	−1.324	−0.038	0.072	−0.527	−0.059	0.072	−0.821	0.052	0.061	0.856	−0.016	0.079	−0.200
Cereals -> MEA	−0.032	0.097	−0.326	0.002	0.084	0.029	0.010	0.073	0.137	−0.016	0.063	−0.258	−0.047	0.086	−0.544	0.255[a]	0.073	3.505	−0.176[a]	0.050	−3.512

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
MEA -> cereals	0.048	0.103	0.466	0.049	0.084	0.584	−0.102	0.075	−1.367	−0.045	0.071	−0.636	−0.052	0.086	−0.607	−0.018	0.081	−0.218	−0.166[a]	0.049	−3.358
Cereals -> North.Am	−0.095	0.086	−1.099	0.039	0.087	0.446	−0.004	0.081	−0.054	−0.047	0.071	−0.664	−0.043	0.088	−0.484	−0.137[c]	0.072	−1.902	−0.114[b]	0.055	−2.092
North.Am -> cereals	−0.188[b]	0.091	−2.066	0.074	0.093	0.801	−0.091	0.081	−1.118	−0.037	0.079	−0.465	−0.051	0.087	−0.589	−0.141[a]	0.067	−2.104	−0.088	0.078	−1.123
Dairy																					
Dairy -> Asia	−0.029	0.094	−0.306	0.030	0.115	0.264	0.069	0.092	0.752	−0.032	0.066	−0.487	−0.050	0.081	−0.625	−0.054	0.079	−0.680	−0.227[a]	0.078	−2.916
Asia -> dairy	0.152[c]	0.091	1.659	0.268[a]	0.080	3.344	0.002	0.092	0.016	−0.020	0.092	−0.222	−0.040	0.083	−0.479	−0.043	0.082	−0.524	−0.234[a]	0.076	−3.058
Dairy -> Asia.Pfc	−0.046	0.095	−0.485	−0.130	0.114	−1.146	0.076	0.090	0.847	−0.037	0.067	−0.563	−0.087	0.081	−1.074	−0.061	0.086	−0.714	−0.039	0.076	−0.508
Asia.Pfc -> dairy	0.143	0.096	1.478	0.108	0.080	1.337	−0.021	0.092	−0.230	−0.031	0.090	−0.345	0.021	0.079	0.263	−0.055	0.083	−0.660	−0.041	0.075	−0.547
Dairy -> BRIC	−0.011	0.108	−0.099	−0.126	0.115	−1.089	0.008	0.088	0.096	−0.035	0.067	−0.528	−0.038	0.077	−0.491	−0.067	0.085	−0.790	−0.084	0.087	−0.963
BRIC -> dairy	0.066	0.089	0.738	0.097	0.078	1.253	−0.101	0.091	−1.113	−0.029	0.087	−0.332	−0.038	0.070	−0.543	−0.048	0.077	−0.623	−0.117[b]	0.055	−2.149
Dairy -> Dev.Mkt	0.057	0.093	0.613	−0.108	0.117	−0.920	0.071	0.085	0.835	−0.034	0.072	−0.477	0.070	0.082	0.848	−0.041	0.089	−0.467	−0.114	0.083	−1.372
Dev.Mkt -> dairy	0.181[c]	0.095	1.905	0.119	0.079	1.503	0.083	0.086	0.962	−0.032	0.072	−0.442	0.051	0.080	0.641	−0.059	0.076	−0.776	−0.115	0.077	−1.483
Dairy -> Emg	−0.009	0.099	−0.095	−0.106	0.109	−0.968	0.005	0.087	0.054	−0.038	0.073	−0.519	−0.034	0.082	−0.411	−0.049	0.086	−0.564	−0.115	0.075	−1.531
Emg -> dairy	0.045	0.097	0.462	0.104	0.081	1.284	−0.083	0.095	−0.869	−0.050	0.091	−0.548	−0.056	0.074	−0.760	−0.038	0.080	−0.479	−0.098	0.088	−1.123
Dairy -> Eur	−0.048	0.103	−0.464	−0.118	0.119	−0.991	0.052	0.093	0.559	−0.037	0.077	−0.489	−0.043	0.090	−0.477	−0.064	0.083	−0.771	0.265[a]	0.092	2.887
Eur -> dairy	−0.001	0.087	−0.011	0.103	0.070	1.463	0.063	0.085	0.743	−0.031	0.069	−0.445	−0.049	0.078	−0.626	−0.040	0.086	−0.467	−0.021	0.083	−0.259
Dairy -> EurZ	−0.015	0.107	−0.143	−0.110	0.104	−1.057	0.065	0.091	0.720	−0.029	0.061	−0.478	−0.025	0.082	−0.300	0.031	0.079	0.394	−0.045	0.084	−0.534
EurZ -> dairy	0.148	0.090	1.642	0.101	0.071	1.427	0.068	0.095	0.713	−0.040	0.078	−0.519	−0.057	0.068	−0.845	0.309[a]	0.085	3.635	−0.023	0.099	−0.227
Dairy -> global market	0.060	0.095	0.634	0.046	0.115	0.399	0.053	0.075	0.708	0.073	0.079	0.920	−0.071	0.083	−0.857	−0.146[c]	0.085	−1.710	−0.093	0.081	−1.146
Global market -> dairy	−0.060	0.086	−0.692	0.142	0.093	1.527	−0.016	0.080	−0.202	−0.075	0.069	−1.085	0.301[a]	0.083	3.638[a]	−0.144[c]	0.077	−1.872	−0.112[b]	0.049	−2.301
Dairy -> Lat.Am	−0.016	0.099	−0.162	−0.088	0.112	−0.788	−0.010	0.079	−0.126	−0.042	0.068	−0.613	−0.035	0.085	−0.414	−0.042	0.081	−0.512	0.258[a]	0.091	2.847

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Lat.Am -> dairy	0.038	0.094	0.408	−0.065	0.079	−0.828	0.027	0.090	0.301	−0.047	0.078	−0.599	−0.038	0.065	−0.591	−0.051	0.065	−0.792	−0.023	0.084	−0.271
Dairy -> MEA	−0.106	0.095	−1.120	0.012	0.109	0.109	0.007	0.084	0.084	−0.032	0.071	−0.446	0.018	0.076	0.238	−0.035	0.080	−0.441	−0.088	0.081	−1.075
MEA -> dairy	−0.007	0.096	−0.077	−0.053	0.078	−0.683	0.028	0.084	0.332	−0.027	0.078	−0.341	0.004	0.088	0.050	0.258[a]	0.077	3.332	−0.120[a]	0.049	−2.464
Dairy -> North.Am	0.048	0.096	0.503	−0.117	0.112	−1.039	−0.037	0.090	−0.413	−0.028	0.072	−0.394	−0.060	0.079	−0.763	−0.032	0.079	−0.407	−0.124	0.083	−1.485
North.Am -> dairy	0.160[c]	0.087	1.834	0.102	0.090	1.128	−0.043	0.096	−0.451	−0.026	0.077	−0.341	−0.047	0.089	−0.529	−0.062	0.064	−0.963	−0.112	0.080	−1.404
Food																					
Food -> Asia	0.103	0.089	1.162	−0.052	0.085	−0.612	0.042	0.086	0.488	−0.004	0.072	−0.061	0.011	0.084	0.126	−0.061	0.083	−0.733	−0.116[b]	0.052	−2.245
Asia -> food	0.132	0.095	1.381	−0.021	0.094	−0.217	0.157[c]	0.082	1.899	−0.074	0.080	−0.923	0.123	0.081	1.518	−0.067	0.082	−0.813	−0.078	0.084	−0.929
Food -> Asia.Pfc	0.117	0.098	1.188	0.048	0.094	0.511	0.032	0.086	0.372	−0.009	0.071	−0.133	0.083	0.083	1.012	−0.052	0.075	−0.698	−0.115[b]	0.050	−2.278
Asia.Pfc -> food	0.125	0.109	1.150	0.058	0.091	0.632	0.148[c]	0.082	1.819	−0.066	0.081	−0.808	0.051	0.079	0.647	−0.063	0.083	−0.767	−0.078	0.082	−0.961
Food -> BRIC	−0.009	0.086	−0.105	0.072	0.088	0.818	−0.046	0.084	−0.550	0.155[b]	0.075	2.077	−0.023	0.081	−0.278	−0.032	0.078	−0.417	−0.169[a]	0.047	−3.588
BRIC -> food	0.091	0.097	0.940	0.071	0.089	0.801	0.235[a]	0.079	2.984	−0.018	0.078	−0.230	−0.049	0.073	−0.675	0.252	0.086	2.938[a]	−0.170[a]	0.050	−3.390
Food -> Dev.Mkt	0.133	0.096	1.379	0.041	0.092	0.449	−0.192	0.080	−2.409	0.163[b]	0.073	2.235	−0.003	0.083	−0.036	0.009	0.082	0.108	−0.120[b]	0.053	−2.248
Dev.Mkt -> food	0.129	0.093	1.385	0.072	0.090	0.801	0.084	0.071	1.181	0.248[a]	0.075	3.314	0.063	0.078	0.797	0.139	0.062	2.218[b]	−0.094	0.081	−1.158
Food -> Emg	0.037	0.089	0.418	0.066	0.095	0.692	−0.139[c]	0.077	−1.817	0.151[b]	0.068	2.225	0.031	0.087	0.362	0.116	0.083	1.405	−0.123[b]	0.049	−2.487
Emg -> food	0.053	0.105	0.506	0.078	0.079	0.986	0.229[a]	0.080	2.872	−0.019	0.084	−0.228	0.004	0.069	0.060	0.014	0.079	0.176	−0.099	0.074	−1.334
Food -> Eur	0.130	0.101	1.284	0.066	0.091	0.723	−0.179[b]	0.082	−2.175	0.016	0.076	0.217	−0.041	0.085	−0.479	0.082	0.085	0.961	0.256[a]	0.055	4.657
Eur -> food	0.119	0.096	1.240	0.063	0.085	0.744	0.183[b]	0.075	2.424	0.238[a]	0.061	3.877	−0.062	0.065	−0.965	0.058	0.083	0.697	−0.022	0.071	−0.311
Food -> EurZ	0.115	0.097	1.185	0.074	0.097	0.768	−0.142[c]	0.074	−1.911	0.027	0.056	0.480	−0.033	0.080	−0.414	−0.032	0.085	−0.378	−0.137[a]	0.049	−2.796
EurZ -> food	0.107	0.094	1.131	0.050	0.085	0.590	0.229[a]	0.082	2.798	0.218	0.063	3.441	−0.043	0.077	−0.562	−0.045	0.083	−0.549	−0.088	0.101	−0.871
Food -> global market	0.001	0.082	0.007	0.038	0.087	0.444	0.000	0.064	0.007	0.000	0.079	0.001	0.006	0.083	0.072	−0.060	0.083	−0.718	−0.173[a]	0.049	−3.525

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Global market -> food	0.026	0.101	0.255	−0.025	0.092	−0.270	0.013	0.075	0.171	−0.132[b]	0.066	−1.994	0.010	0.083	0.125	−0.052	0.083	−0.622	−0.161[a]	0.043	−3.789
Food -> Lat.Am	0.212[b]	0.090	2.361	0.016	0.091	0.173	−0.133[c]	0.073	−1.827	0.082	0.059	1.391	−0.034	0.086	−0.396	−0.006	0.081	−0.077	0.251[a]	0.058	4.304
Lat.Am -> food	−0.001	0.104	−0.012	0.013	0.097	0.131	0.060	0.090	0.667	0.078	0.065	1.195	−0.062	0.072	−0.869	0.050	0.075	0.670	−0.015	0.083	−0.175
Food -> MEA	0.103	0.090	1.150	0.053	0.086	0.619	−0.139[c]	0.075	−1.870	0.065	0.071	0.920	−0.039	0.077	−0.502	−0.017	0.086	−0.194	−0.175[a]	0.045	−3.857
MEA -> food	0.028	0.096	0.287	0.167[c]	0.093	1.789	0.144	0.072	2.001	0.258[c]	0.071	3.612	−0.049	0.077	−0.639	0.016	0.075	0.208	−0.166[a]	0.050	−3.336
Food -> North.Am	0.140	0.092	1.526	0.050	0.089	0.564	−0.119	0.088	−1.349	0.044	0.072	0.613	−0.053	0.082	−0.643	−0.065	0.082	−0.802	−0.105[b]	0.048	−2.177
North.Am -> food	0.134	0.091	1.472	0.096	0.104	0.931	−0.032	0.086	−0.369	−0.081	0.067	−1.208	−0.057	0.078	−0.732	0.051	0.069	0.745	−0.087	0.078	−1.113
Meat																					
Meat -> Asia	0.065	0.084	0.774	−0.020	0.091	−0.224	−0.035	0.082	−0.434	0.069	0.071	0.974	−0.054	0.083	−0.656	−0.056	0.077	−0.729	−0.037	0.098	−0.384
Asia -> meat	0.096	0.090	1.074	0.164[c]	0.086	1.896	−0.119	0.080	−1.493	0.074	0.082	0.901	−0.061	0.084	−0.735	−0.054	0.083	−0.656	−0.051	0.082	−0.616
Meat -> Asia.Pfc	0.061	0.087	0.705	−0.010	0.098	−0.101	−0.139[c]	0.080	−1.730	0.057	0.075	0.750	−0.042	0.086	−0.490	−0.046	0.075	−0.604	−0.032	0.100	−0.324
Asia.Pfc -> meat	0.095	0.107	0.890	0.189[c]	0.097	1.941	−0.034	0.072	−0.472	0.079	0.088	0.903	−0.056	0.084	−0.661	−0.054	0.081	−0.669	−0.052	0.081	−0.645
Meat -> BRIC	−0.066	0.090	−0.727	−0.082	0.100	−0.819	−0.037	0.082	−0.457	0.032	0.067	0.477	−0.030	0.085	−0.354	−0.044	0.076	−0.584	−0.095	0.097	−0.978
BRIC -> meat	0.033	0.099	0.335	0.216[b]	0.090	2.418	−0.029	0.070	−0.417	0.034	0.090	0.380	−0.058	0.076	−0.765	−0.056	0.080	−0.705	−0.126[a]	0.045	−2.815
Meat -> Dev.Mkt	0.074	0.085	0.864	0.024	0.093	0.262	0.027	0.072	0.373	−0.131[c]	0.072	−1.809	0.020	0.095	0.208	−0.025	0.076	−0.335	−0.036	0.101	−0.356
Dev.Mkt -> meat	0.096	0.083	1.157	0.109	0.095	1.147	−0.006	0.065	−0.088	−0.122	0.076	−1.604	0.003	0.088	0.036	−0.070	0.060	−1.152	−0.059	0.085	−0.695
Meat -> Emg	0.020	0.091	0.219	−0.146	0.098	−1.482	−0.019	0.073	−0.267	0.036	0.065	0.549	−0.034	0.083	−0.404	−0.049	0.075	−0.649	−0.034	0.104	−0.331
Emg -> meat	0.027	0.092	0.297	0.093	0.093	1.001	−0.031	0.081	−0.383	0.032	0.093	0.348	−0.065	0.066	−0.994	−0.062	0.077	−0.810	−0.061	0.082	−0.748
Meat -> Eur	0.041	0.098	0.417	0.003	0.095	0.032	0.020	0.076	0.265	0.041	0.072	0.565	−0.039	0.066	−0.587	−0.055	0.092	−0.591	0.116	0.097	1.201
Eur -> meat	0.028	0.099	0.287	0.186[b]	0.089	2.093	−0.007	0.071	−0.092	−0.065	0.066	−0.978	−0.064	0.064	−1.007	−0.058	0.085	−0.692	−0.019	0.079	−0.241
Meat -> EurZ	−0.018	0.092	−0.196	−0.006	0.101	−0.056	0.018	0.078	0.235	0.132[c]	0.069	1.905	−0.024	0.070	−0.339	0.241	0.089	2.711	−0.120	0.094	−1.275
EurZ -> meat	0.088	0.096	0.913	0.168[b]	0.083	2.025	−0.017	0.067	−0.252	−0.047	0.073	−0.640	−0.063	0.064	−0.988	−0.029	0.084	−0.339	−0.119	0.101	−1.185

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Meat -> global market	0.027	0.077	0.349	−0.109	0.103	−1.058	0.085	0.066	1.292	−0.094	0.085	−1.116	−0.027	0.083	−0.325	0.019	0.085	0.228	−0.091	0.093	−0.975
Global market -> meat	−0.043	0.095	−0.449	−0.096	0.098	−0.973	−0.018	0.075	−0.246	−0.030	0.065	−0.460	0.256[a]	0.075	3.438	−0.011	0.081	−0.133	−0.127[b]	0.050	−2.543
Meat -> Lat.Am	0.017	0.088	0.191	−0.094	0.095	−0.990	−0.020	0.077	−0.255	0.019	0.065	0.289	−0.032	0.081	−0.394	−0.034	0.078	−0.443	0.114	0.100	1.145
Lat.Am -> meat	0.037	0.092	0.400	0.179[b]	0.086	2.066	−0.008	0.072	−0.108	−0.046	0.069	−0.666	−0.068	0.066	−1.033	−0.053	0.068	−0.786	−0.008	0.079	−0.102
Meat -> MEA	0.032	0.088	0.366	−0.104	0.088	−1.187	0.019	0.066	0.289	−0.133[b]	0.067	−1.994	−0.051	0.081	−0.629	−0.058	0.088	−0.662	−0.085	0.091	−0.942
MEA -> meat	−0.070	0.090	−0.779	0.021	0.089	0.235	−0.023	0.070	−0.329	−0.131[c]	0.078	−1.674	−0.053	0.081	−0.651	−0.046	0.089	−0.521	−0.123[b]	0.052	−2.342
Meat -> North.Am	−0.043	0.087	−0.491	0.001	0.094	0.008	−0.002	0.083	−0.020	0.017	0.062	0.279	−0.052	0.077	−0.675	−0.031	0.093	−0.336	−0.040	0.093	−0.434
North.Am -> meat	0.103	0.093	1.104	0.024	0.100	0.241	−0.010	0.073	−0.138	−0.083	0.068	−1.228	−0.056	0.071	−0.798	−0.064	0.064	−1.005	−0.039	0.078	−0.509
Veg. oil																					
Veg. oil -> Asia	0.015	0.099	0.150	−0.102	0.084	−1.212	0.041	0.084	0.487	0.154[b]	0.065	2.355	−0.054	0.083	−0.654	−0.050	0.082	−0.611	−0.120	0.086	−1.408
Asia -> veg. oil	0.034	0.095	0.365	0.004	0.086	0.046	0.149[c]	0.077	1.940	−0.010	0.090	−0.113	−0.050	0.079	−0.627	−0.053	0.077	−0.687	−0.114	0.078	−1.475
Veg. oil -> Asia.Pfc	0.013	0.086	0.145	−0.110	0.086	−1.275	−0.054	0.089	−0.603	0.158[a]	0.061	2.606	−0.049	0.085	−0.581	−0.059	0.078	−0.755	−0.048	0.079	−0.611
Asia.Pfc -> veg. oil	0.015	0.099	0.155	0.004	0.089	0.040	0.144[c]	0.082	1.756	−0.015	0.086	−0.181	−0.053	0.089	−0.599	−0.051	0.082	−0.621	−0.044	0.076	−0.575
Veg. oil -> BRIC	−0.093	0.098	−0.955	0.012	0.091	0.127	−0.027	0.083	−0.323	0.040	0.063	0.638	−0.033	0.089	−0.376	−0.062	0.093	−0.662	−0.090	0.079	−1.138
BRIC -> veg. oil	−0.035	0.096	−0.363	0.201[b]	0.086	2.332	0.074	0.081	0.910	0.008	0.081	0.104	−0.054	0.072	−0.761	−0.058	0.083	−0.699	−0.116[b]	0.048	−2.402
Veg. oil -> Dev.Mkt	0.125	0.091	1.367	−0.063	0.091	−0.695	−0.131[c]	0.074	−1.775	0.061	0.064	0.959	0.018	0.086	0.207	−0.036	0.078	−0.460	−0.111	0.083	−1.335
Dev.Mkt -> veg. oil	0.035	0.092	0.382	−0.033	0.088	−0.373	0.059	0.082	0.723	0.008	0.069	0.110	0.018	0.091	0.202	−0.055	0.070	−0.787	−0.121	0.077	−1.574
Veg. oil -> Emg	−0.021	0.096	−0.222	0.028	0.096	0.296	−0.200[b]	0.079	−2.529	0.037	0.071	0.522	−0.047	0.083	−0.567	−0.055	0.083	−0.656	−0.121	0.075	−1.613
Emg -> veg. oil	0.032	0.100	0.322	0.208[b]	0.092	2.259	0.063	0.076	0.824	0.012	0.081	0.152	−0.056	0.072	−0.776	−0.053	0.092	−0.575	−0.115	0.074	−1.558
Veg. oil -> Eur	0.106	0.099	1.069	−0.077	0.087	−0.886	−0.038	0.080	−0.475	0.003	0.065	0.053	−0.046	0.073	−0.637	−0.060	0.090	−0.661	0.269[a]	0.088	3.053

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Eur -> veg. oil	0.013	0.087	0.154	0.005	0.086	0.053	0.147[c]	0.080	1.839	0.463[a]	0.073	6.325	−0.058	0.068	−0.849	−0.056	0.076	−0.738	−0.023	0.082	−0.282
Veg. oil -> EurZ	0.028	0.094	0.304	−0.070	0.092	−0.767	−0.056	0.081	−0.685	−0.041	0.074	−0.552	−0.024	0.087	−0.271	−0.050	0.085	−0.591	−0.061	0.083	−0.730
EurZ -> veg. oil	0.109	0.094	1.157	−0.007	0.081	−0.085	0.264[a]	0.079	3.348	0.223[a]	0.065	3.437	−0.046	0.067	−0.694	−0.052	0.084	−0.623	−0.032	0.092	−0.351
Veg. oil -> global market	0.102	0.090	1.133	0.045	0.091	0.500	0.062	0.072	0.862	0.064	0.081	0.786	−0.023	0.090	−0.252	−0.044	0.086	−0.508	−0.092	0.083	−1.120
Global market -> veg. oil	0.037	0.081	0.458	−0.049	0.097	−0.507	−0.033	0.076	−0.432	0.025	0.061	0.403	0.259[a]	0.082	3.163	−0.064	0.087	−0.739	−0.119[b]	0.050	−2.398
Veg. oil -> Lat.Am	0.040	0.091	0.440	0.066	0.091	0.725	−0.189	0.073	−2.592	−0.032	0.066	−0.480	−0.034	0.083	−0.407	−0.040	0.080	−0.504	0.246[a]	0.088	2.796
Lat.Am -> veg. oil	0.106	0.093	1.145	0.033	0.089	0.369	−0.007	0.086	−0.084	0.011	0.068	0.164	−0.052	0.075	−0.703	−0.056	0.068	−0.816	−0.024	0.079	−0.307
Veg. oil -> MEA	0.035	0.094	0.377	−0.035	0.080	−0.436	−0.196[a]	0.076	−2.590	0.057	0.072	0.788	−0.052	0.088	−0.590	−0.044	0.071	−0.616	−0.092	0.077	−1.203
MEA -> veg. oil	0.098	0.098	1.004	0.175[c]	0.090	1.932	0.154	0.075	2.049	0.010	0.075	0.128	−0.062	0.084	−0.732	−0.055	0.080	−0.686	−0.123[b]	0.056	−2.175
Veg. oil -> North.Am	0.114	0.092	1.241	−0.041	0.085	−0.479	−0.076	0.084	−0.911	0.032	0.074	0.433	−0.041	0.077	−0.535	−0.029	0.089	−0.328	−0.116	0.077	−1.499
North.Am -> veg. oil	0.122	0.091	1.339	−0.043	0.091	−0.470	−0.061	0.088	−0.687	−0.060	0.063	−0.957	−0.056	0.077	−0.730	−0.074	0.070	−1.059	−0.123	0.080	−1.541
Sugar																					
Sugar -> Asia	0.136	0.098	1.395	−0.145	0.093	−1.566	0.034	0.091	0.367	−0.043	0.065	−0.669	−0.048	0.054	−0.881	0.008	0.079	0.102	−0.112	0.075	−1.486
Asia -> sugar	0.079	0.095	0.829	−0.124	0.082	−1.522	0.138	0.084	1.642	−0.026	0.080	−0.325	−0.019	0.088	−0.215	0.010	0.086	0.111	−0.114	0.078	−1.466
Sugar -> Asia.Pfc	0.156[c]	0.093	1.677	−0.199[a]	0.098	−2.022	0.052	0.084	0.619	−0.041	0.066	−0.624	−0.069	0.065	−1.064	−0.035	0.087	−0.397	−0.111	0.080	−1.394
Asia.Pfc -> sugar	0.056	0.092	0.605	−0.043	0.086	−0.502	0.146[c]	0.079	1.860	−0.052	0.093	−0.554	−0.015	0.092	−0.163	0.260[a]	0.080	3.259	−0.119	0.080	−1.476
Sugar -> BRIC	0.161	0.105	1.539	−0.081	0.101	−0.801	−0.045	0.081	−0.557	−0.034	0.074	−0.464	−0.059	0.072	−0.818	0.042	0.082	0.517	−0.082	0.080	−1.025
BRIC -> sugar	0.159[c]	0.084	1.885	0.085	0.089	0.956	0.066	0.086	0.766	−0.033	0.080	−0.415	0.042	0.075	0.559	−0.011	0.079	−0.145	−0.117[b]	0.051	−2.285
Sugar -> Dev.Mkt	0.156[c]	0.088	1.772	−0.064	0.100	−0.639	−0.142[c]	0.079	−1.790	−0.025	0.069	−0.364	−0.099[c]	0.058	−1.695	0.037	0.090	0.412	−0.116	0.076	−1.532
Dev.Mkt -> sugar	0.160[c]	0.090	1.788	0.050	0.093	0.538	0.056	0.070	0.792	−0.043	0.078	−0.556	−0.034	0.088	−0.389	0.013	0.070	0.178	−0.116	0.076	−1.525
Sugar -> Emg	0.066	0.096	0.693	−0.076	0.099	−0.771	−0.207[b]	0.083	−2.507	−0.043	0.070	−0.618	0.005	0.062	0.081	−0.033	0.079	−0.415	0.263[a]	0.081	3.260

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Emg -> sugar	0.074	0.094	0.784	0.075	0.091	0.824	0.058	0.081	0.720	−0.037	0.085	−0.438	−0.034	0.074	−0.463	−0.061	0.088	−0.692	−0.102	0.078	−1.307
Sugar -> Eur	0.095	0.098	0.969	−0.120	0.101	−1.194	−0.048	0.076	−0.629	−0.046	0.072	−0.637	−0.138	0.060	−2.314	−0.071	0.076	−0.944	0.251[a]	0.081	3.118
Eur -> sugar	−0.014	0.094	−0.146	−0.045	0.080	−0.567	0.148[c]	0.077	1.924	−0.029	0.073	−0.391	−0.022	0.075	−0.300	−0.059	0.090	−0.661	−0.022	0.084	−0.264
Sugar -> EurZ	0.121	0.100	1.219	−0.127	0.088	−1.437	−0.056	0.076	−0.736	−0.052	0.072	−0.719	−0.156[b]	0.064	−2.419	−0.054	0.076	−0.708	−0.054	0.081	−0.663
EurZ -> sugar	0.036	0.095	0.380	−0.064	0.080	−0.794	0.260[a]	0.077	3.372	−0.035	0.068	−0.519	−0.017	0.061	−0.279	−0.059	0.082	−0.716	−0.033	0.098	−0.336
Sugar -> global market	0.150[c]	0.086	1.741	−0.026	0.094	−0.278	−0.017	0.069	−0.249	−0.016	0.079	−0.207	−0.052	0.072	−0.723	0.117	0.079	1.474	−0.089	0.082	−1.079
Global market -> sugar	−0.193[b]	0.091	−2.128	−0.019	0.097	−0.193	0.011	0.075	0.147	0.023	0.061	0.381	−0.123	0.089	−1.375	0.008	0.088	0.091	−0.109	0.046	−2.374
Sugar -> Lat.Am	0.112	0.095	1.174	−0.120	0.102	−1.182	−0.176[b]	0.075	−2.364	−0.043	0.071	−0.613	0.162[a]	0.062	2.610	−0.036	0.085	−0.427	0.249[a]	0.089	2.808
Lat.Am -> sugar	0.028	0.087	0.319	0.144[c]	0.083	1.727	0.009	0.087	0.106	−0.026	0.071	−0.370	0.067	0.076	0.888	−0.053	0.069	−0.759	−0.010	0.087	−0.115
Sugar -> MEA	0.213[b]	0.092	2.318	−0.084	0.100	−0.839	−0.197[b]	0.077	−2.552	−0.035	0.067	−0.517	0.062	0.063	0.990	−0.059	0.078	−0.758	−0.084	0.080	−1.051
MEA -> sugar	0.204[b]	0.093	2.199	0.060	0.080	0.754	0.149[c]	0.077	1.952	−0.018	0.069	−0.256	−0.070	0.089	−0.789	−0.056	0.083	−0.671	−0.105[c]	0.055	−1.926
Sugar -> North.Am	0.133	0.088	1.522	0.007	0.107	0.070	−0.075	0.087	−0.868	−0.046	0.064	−0.716	0.124[b]	0.062	1.989	0.015	0.086	0.173	−0.120	0.078	−1.532
North.Am -> sugar	0.154[c]	0.087	1.762	0.031	0.097	0.320	−0.043	0.079	−0.542	−0.039	0.070	−0.564	−0.045	0.083	−0.535	0.015	0.067	0.216	−0.124	0.078	−1.599

Notes. Asia.Pfc: Asia-Pacific; Dev.Mkt: developed markets; Emg: emerging markets; Eur: Europe markets; EurZ: Eurozone; Lat.Am: Latin America; North.Am: North America. Significance levels are [a](1%), [b](5%), and [c](10%). ETE – effective transfer entropy; SE – standard error; T-stats – the resultant *t*-statistics of ETEs.

quite a long period, they tend to start getting saturated with information transfer. Ideally, reassessing the performance of commodities and equities in a given portfolio is key to minimising portfolio and cross-market risks through information transfer. This emphasises the heterogeneity of cross-asset linkages, as revealed in the empirical literature on commodity and stock markets (see, e.g., [44, 45, 57–60, 78]). This is not surprising since the effect of significant or key events in the medium term is likely to arouse market linkages [9]. Thus, though some diversification prospects are found, they may last with the duration of the key events. Impliedly, vanishing diversification potentials may correspond to the emergence and passage of key events in the medium term [8, 9, 80].

We now turn to the long-term ETEs, the residual. For cereals and food, except those of Latin America and Europe (which are positive ETE recipients), all other regional equities are negative ETE recipients. Equities from the Middle East and Africa, global markets, Eurozone, developed markets, Asia and the Asia-Pacific, emerging markets, and North America are significant diversifiers for cereals and food; between equities, they are diversification candidates for stocks from Latin America and Europe. The Middle East and Africa, global markets, and BRIC markets transmit negative ETEs to cereals, making them significant diversifiers with both cereals and food. Upon shocks to the dairy market, Asian stocks are significant diversifiers, which further create diversification pairs with equities from Latin America and Europe. Amid equity market shocks, Asia, global, Middle East and Africa, and BRIC markets could diversify with dairy.

For meat, vegetable oil, and sugar, no significant diversification pairs are available when the commodity markets experience shocks. However, when equity markets are affected by shocks, equities from BRIC, global markets, and the Middle East and Africa could be diversified with any meat, vegetable oil, and sugar. In the long term, we find more significant diversification potentials between food commodity markets and regional and/or global equities. We attribute this to the fundamental properties of commodities as diversifiers for traditional assets [79]. The intuition is that as Yang et al. [80] espouse, the long-term is driven by fundamentals between markets, it is expected that regardless of the effects of investor sentiments and key events, the information flow between commodity markets and regional and global equity markets would most likely result from the fundamental dynamics that apply in all markets.

The results in the frequency domain reveal more significant ETEs relative to those of the composite, which only revealed a diversification opportunity between sugar and global equity markets. Impliedly, frequency-domain analysis unveils hidden significant ETEs at the composite level. This suggests that taking into consideration the heterogeneity of commodity markets and market players alike [3, 50, 57, 60, 79], the essence of the frequency-domain analysis cannot be downplayed.

From Table 2, we find that cereals and dairy markets could either diversify with or be diversified by global equities nearing the end of the mid term or in the long term only. Thus, should either market (cereals or dairy) experience shocks, regional and global equities may provide diversification benefits. Similarly, in times of shocks to regional and global equities, cereals and dairy could offer a safety net for international investors. However, these could manifest in the long term only.

Moreover, we report that food and meat markets stand the chance to offer diversification opportunities in the latter part of the short and long terms only. In the short term, diversification opportunities for portfolios containing food and meat are likely to achieve mixed combinations between commodities and stocks as well as between equities alone. Similar opportunities avail in the long term, but for the meat market, such opportunities are largely between meat and equity markets since the chances for all equity diversification are very slim. The results for the meat market are more likened to that of the vegetable oil market, which also reveals diversification prospects between oil and regional and global equity markets in the short- and long-term periods only. The stand out agricultural commodity market from the FAO indices is that of sugar. We report that sugar provides diversification opportunities with regional and global equity markets generally across all time horizons. Thus, there is a high tendency to use global equities to hedge against losses from the sugar market in times of crisis, and sugar could also hedge against the losses from global equities amid crises periods. Table 3 summarises the diversification prospects between world food commodities and regional equities resulting from information flow.

5.3. Economic Implications of the Results. Per the competitive markets hypothesis, information flow between markets intensify due to the behaviour of market participants [9]. Since the behaviour of these market participants evolves, our results are essential to investors who trade along timelines corresponding to the short-, medium-, and long-term horizons. Notably, at the composite level, where no assumption is made about the complexity and nonlinearity of the data series, we identify that investors could only resort to investments in global stocks and sugar for diversification when the traditional stock market experiences any shock. Aside from sugar and global equities, all other food commodities and equity markets have no significant diversification potential at the composite level. The assumption at the composite level is that market participants respond equally to market dynamics. This assumption is inconsistent with Mongars and Marchal-Dombrat's [81] observation that investor response to commodity market dynamics is heterogeneous, and this is consistent with the conclusions made by recent works [3, 41, 43, 57, 60, 61, 78, 79]. The frequency-domain analysis overcomes this limitation.

Speculators and hedgers are interested in short-term gains, whereas the interest of institutional investors lies in long-term returns. In between short- and long-term investors are medium-term investors, who regularly monitor and rebalance their portfolios to take advantage of medium-term gains. Our results in the frequency domain make a relevant contribution as key inputs for investment decisions based on time scales. Specifically, in the short term, our

Table 3: Summary of results.

Series	Commodity	Diversification potentials			
		Shocks to commodity markets		Shocks to equity markets	
		Commodity vs. equities	Between equities	Commodity vs. equities	Between equities
Composite	Cereals	✗	✗	North America vs. cereals	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	✗	✗	Global markets vs. sugar	Global markets vs. North America, developed markets, BRIC, and MEA
IMF1, short term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	Sugar vs. Asia-Pacific	✗	✗	✗
IMF2, short term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	Food vs. developed markets, European, Eurozone, MEA, emerging markets, and Latin America	✗	✗	✗
	Meat	Meat vs. Asia-Pacific	✗	✗	✗
	Veg. oil	Veg. oil vs. emerging, MEA, Latin America, and developed markets	✗	✗	✗
	Sugar	Sugar vs. emerging markets, MEA, Latin America, and developed markets	✗	✗	✗
IMF3, mid term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	Food vs. global market	Global vs. global vs. Europe, Eurozone, MEA, and developed markets)
	Meat	Meat vs. MEA and developed markets	MEA and developed markets vs. Eurozone	Meat vs. MEA	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	✗	✗	✗	✗
IMF4, mid term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	Sugar vs. developed, Eurozone, and Europe	Developed, Eurozone, and Europe vs. North America and Latin America	✗	✗

Table 3: Continued.

Series	Commodity	Diversification potentials			
		Shocks to commodity markets		Shocks to equity markets	
		Commodity vs. equities	Between equities	Commodity vs. equities	Between equities
IMF5, mid term	Cereals	Cereals vs. North America and Latin America	North American and Latin America vs. MEA	Cereals vs. North America	North America vs. emerging and developed markets
	Dairy	Dairy vs. global markets	✗	Dairy vs. global	Global markets vs. developed and Eurozone markets
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	✗	✗	✗	✗
Residual, long term	Cereals	Cereals vs. MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and the Asia-Pacific	MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and Asia-Pacific vs. Latin America and Europe	Cereals vs. MEA, global markets, and BRIC	✗
	Dairy	Dairy vs. Asia	Asia vs. Latin America and Europe	Dairy vs. Asia, global markets, MEA, and BRIC	✗
	Food	Food vs. MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and the Asia Pacific	MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and Asia-Pacific vs. Latin America and Europe	Food vs. MEA, global markets, and BRIC	✗
	Meat	✗	✗	Meat vs. BRIC, global markets, and MEA	✗
	Veg. oil	✗	✗	Veg. oil vs. BRIC, global markets, and MEA	✗
	Sugar	✗	✗	Sugar vs. BRIC, global markets, and MEA	✗

Note: This table presents the summarised diversification or hedging pairs between commodities and regional equities as well as between equities. MEA – the Middle East and Africa and veg. oil – vegetable oil.

findings explicate that cereals, dairy, food, meat, and vegetable oil fail to offer diversification benefits to investors. For speculators and hedgers, investment in sugar may most likely suffice their investment needs, when combined with regional equities.

For medium-term investors, food, meat, and sugar may serve as potential diversifiers for regional or global equities, but their role as diversifiers may be inconsistent owing to the inconsistent significant relationships found with equity markets. Impliedly, portfolios containing investments in food, meat, and sugar should be monitored in the medium term to make effective rebalancing assessments.

On a good note, long-term investors, such as institutional investors, stand the chance of benefiting from all commodity markets. Specifically, cereals, dairy, food, meat, vegetable oil, and sugar consistently serve as diversifiers for regional and global equity investments in the long term. From this observation, we conclude that the fundamental role of commodities as diversifiers [3, 43, 57, 63, 79, 82] is corroborated through information transfer. Thus, based on the intrinsic information shared by commodity and equity markets, the dynamics between the two asset classes revert to their fundamental linkages in the long term.

6. Conclusion

The intrinsic information shared by financial assets provides a means of assessing their mutual linkages. In times of crisis, spillovers and information flow between markets increase, and this drives empirical investigations into the degree of connectedness between financial assets. Commodity markets are seeing growing financialisation into the traditional market due to their ability to offer diversification benefits to traditional assets, and this has been termed the financialisation of commodities. In the wake of COVID-19 and other recent episodes of financial crises, the empirical literature has focused on the return and volatility connectedness between all sorts of commodity markets, with no evidence of the degree of information transfer between them. To

complement the assessments on the competitive market hypothesis, we take the direction of information flow and focus on commodity markets, which have seen several volatilities in recent periods.

From this backdrop, we investigate the situated information transfers between commodity and equity markets' returns by employing the FAO food commodity and its constituents' indices and the regional stock markets. We contribute to the literature on commodity markets by providing empirical evidence on the quantitative information transfers between food commodity and equity markets' returns. Through this analysis, potential diversification benefits between commodity and/or equity markets are revealed across investment scales, which suit the investment needs of short-, medium-, and long-term investors.

Our findings are suggestive of the fact that the behaviour of equity markets could be observed by commodity markets through the mutual information they share, and this helps determine which markets are effective pairs for diversification. Mainly, our results indicate that information flow between commodity and equity markets vary across time scales or frequencies. To inform interested market participants, our composite transfer entropies suggest that out of the food commodity classes, only sugar serves as a significant diversifier. The diversification potentials of cereals, dairy, food, meat, and vegetable oil prove insignificant on the composite scale. Findings from the frequency domain, which provide insightful results for time horizon investors, reveal that cereals and dairy are diversifiers in the long term only; food and meat are significant diversifiers in the short- and long-term periods only; a consistent diversifier across the short-, medium-, and long-term horizons is sugar. These assets diversify with particular regional and/or global equity markets, which should be noted by investors.

Our results have several implications for both private sector investment management techniques and public sector monitoring and policy design. The portfolio concentration risk of private sector investors is directly related to connectedness, and hence, investors should utilise the knowledge about the degree of connection between commodity and equity markets for effective portfolio management. Portfolios should be monitored along with investment time scales, whilst taking into consideration the linkage between assets due to information flow. Furthermore, empirical evidence suggests that the connectedness between commodities intensifies during crises, and this translates to the broader macroeconomy. Hence, regulators should capitalise on the knowledge concerning the information flow between commodity and equity markets in devising and monitoring market policies in the public sector.

From the findings of this study, the quantile dependencies between the studied variables could be explored, as they were unrevealed by the employed methodologies. As a result, future studies could assess the conditional dependence between food commodity and equity markets. The family of quantile regressions may be essential in this regard. Additionally, it would be fascinating to draw inferences from econophysics methodologies such as the detrended cross-correlation analysis [83] and sliding windows detrended fluctuation technique [84], among others.

Data Availability

The food commodity indices are available at https://www.fao.org/; the data on regional stock markets indices are accessible from EquityRT website (https://equityrt.com/).

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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Research Article

Nonlinear Volatility Risk Prediction Algorithm of Financial Data Based on Improved Deep Learning

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With the gradual integration of global economy and finance, the financial market presents many complex financial phenomena. To increase the prediction accuracy of financial data, a new nonlinear volatility risk prediction algorithm is proposed based on the improved deep learning algorithm. First, the financial data are taken as the research object and the closing price is set as the prediction target. Then, the nonlinear volatility risk prediction model of the financial data is established through the wavelet principal component analysis noise reduction module and the long and short-term memory network (LSTM) module, and the nonlinear volatility trend is extracted from multiple financial data series to realize the nonlinear volatility risk prediction of the financial data. During the whole experiment, the time of the research method was less than 1.5 minutes. And for 1200 test samples, the average error of data risk prediction of the proposed method is 0.0217%. The average cost of the research method is 114.25 million yuan, which is significantly lower than other existing algorithms. Experimental results show that the research method can effectively predict the risk of financial data and is more suitable for the risk control early warning of Internet financial platform.

1. Introduction

With the global economic integration, the globalization and liberalization of capital are also in the deepening stage. At the same time, the financial support for economic development is growing, and the financial market has also achieved global integration [1, 2]. Financial innovation, financial technology, or financial market fluctuations can cause large-scale financial crisis in a large range, so risk management has become the focus of the financial field. As an emerging industry with immature development, while the scale of Internet finance is expanding rapidly, the business standardization, management, technology, and other aspects are not perfect enough, and the Internet finance platform uses the platform as the carrier to realize financing and lending. In the whole link, the funds are managed by the platform independently without any third-party guarantee or custody. Therefore, the platform's credit is very important, as any credit problems will result in severe economic losses for investors and perhaps even irreversible consequences. Due to information asymmetry, imperfect credit system, and other reasons, the risks of Internet finance in our country are prominent, and some models even have consequences such as transition and delisting. Therefore, the technology for extracting key early warning factors and the prediction and measurement of risks have become an important research direction.

The volatility prediction of financial assets is the premise of managing and controlling financial market risks. In the context of big data, there is a trend in the integration of big data and financial industry, and in the face of massive financial data, the traditional prediction method of financial market volatility is no longer effective [3–5]. However, the improvement in artificial intelligence theory, Internet Finance, and computer technology has brought new opportunities for the financial market volatility prediction and risk management. Big data is the basis of the development of artificial intelligence, so deep learning and other methods can be introduced into quantitative investment, financial VaR calculation, and other problems [6]. In traditional investment theory, risk is the uncertainty of asset return, which is usually measured by the variance of asset return and the covariance between various asset returns [7–10]. There are three kinds of risks in the financial market: credit risk,

liquidity risk, and market risk. At this stage, relevant experts have carried out research on the nonlinear volatility risk prediction of financial data and achieved relatively significant research results. For example, in reference [11], clustering analysis of customers is carried out using the machine learning algorithm based on customer portrait, then according to the characteristics of different cluster customers and based on different attributes of the bank financial business, the demands and values of customers are mined. It also helps the bank to formulate the marketing strategy with personalized tag, so as to achieve the goal of precise marketing promotion [12–15]. At the same time, the classification prediction model is constructed to predict the customers with loss risk in the sample data. In reference [16], FIGARCH model is used to effectively deal with the heteroscedasticity of volatility, and extreme value theory (EVT) method with long-term memory is used to accurately fit the advantages of asset return distribution, so as to achieve financial data risk prediction. This algorithm only takes time as an independent variable and then granulates the time information. Each time information particle contains the lowest value, the highest value, and the average value. According to the time series, it predicts the fluctuation range of stocks. However, the above methods cannot meet the current development needs. Reference [17] proposes that the first mock exam of the financial time series data and the local correlation characteristics of the time series data of different financial markets be incorporated into the same model, and the CNN-GRU neural network with the advantages of convolution neural network (CNN) and gated circulation unit (GRU) neural network is constructed. At the same time, the integrated empirical mode decomposition and run length judgment method are used to decompose and reconstruct the financial time series data into trend items, low-frequency items, and high-frequency items, so as to construct the financial time series data prediction model based on different frequencies and fluctuations and then integrate the prediction results of different components to obtain the final prediction results. However, because this method does not consider the noise problem of financial data, there are some deviations in the sequence prediction results of data, which affects the application effect of this method.

To this end, a nonlinear volatility risk prediction algorithm is proposed based on the improved depth learning algorithm.

2. Nonlinear Volatility Risk Prediction Algorithm of Financial Data

2.1. Risk Prediction Model Construction Based on Volatility. Volatility is a changing economic form, that is, an indicator reflecting the change of an economic variable, or a description of the change range of a variable. All things in nature have their own unique existence, such as apples on the table, which express their existence form to the outside world through color, fragrance, taste, and shape, while volatility, as an abstract and expression of the entity of volatility, shows the structure of a variable fluctuation and the change of this kind of fluctuation. The focus of volatility is often placed on the structure of the entity of volatility, so eventually volatility becomes a natural rate, which can also be said to be an incredible geometric rate [18–20].

Volatility is defined statistically as the standard deviation of asset returns in unit time under continuous compound interest.

In economic sense, there are three reasons for volatility: (1) systematic risk, (2) nonsystematic risk, and (3) changes in psychological state or expectations of investors. It can be seen that in any case, volatility is always a variable [21–25].

Stochastic process is a family of random variables that change with time parameters [26]. Stochastic process is related to time, and it is a function of time t, in which t is a parameter. Stochastic process is the whole of possible realization. Suppose (Ω, F, P) is a probability space. For each parameter $t \in T$, $X(t, \omega)$ is a random variable, which is called a family of random variables.

$$X_T = [X(t, \omega), t \in T]. \tag{1}$$

From the perspective of financial time series analysis, stochastic process is introduced. Starting from stochastic probability theory, stochastic process is a set of a series or a group of random variables (or random functions), which is used to describe the realization results of random phenomena in the process of continuous observation. For each observation, the random variable is obtained once [27, 28]. If this observation lasts forever over time, a family or set of random variables, or a random process, can be obtained to describe the continuous evolution of random phenomena.

In practical application, the random variables that make up the stochastic process are generally defined in time domain or space domain. The examples of stochastic process include the fluctuation of stock, interest rate, and exchange rate with time. Assuming that the stock price with sample size T has changed Y_t, then:

$$Y_t = \{y_1, y_2, \cdots, y_n\}. \tag{2}$$

Deep learning neural network is produced in the research process of artificial neural network [29, 30]. Through combining low-level features, deep learning transforms it into high-level, more abstract features and categories, so as to find the distributed feature representation of data. There are many types of deep neural networks. In this article, LSTM is applied to extract the characteristics of financial data.

Because RNN neural network is difficult to solve the problem of gradient disappearance in extended software, a long-term and short-term memory network is proposed. Long and short-term memory is based on RNN neural network. Memory unit and state mechanism of hidden layer are introduced to control the error of financial data transfer between hidden layers. On this basis, we add a gate control mechanism to judge whether the financial data is remembered or forgotten, so as to solve the transitional fitting problem in the process of financial data processing. The unit structure of the network is shown in Figure 1.

The financial data input by time t first obtains the value of time t memory cell output layer and the final memory cell output value through the input gate, the process is as follows:

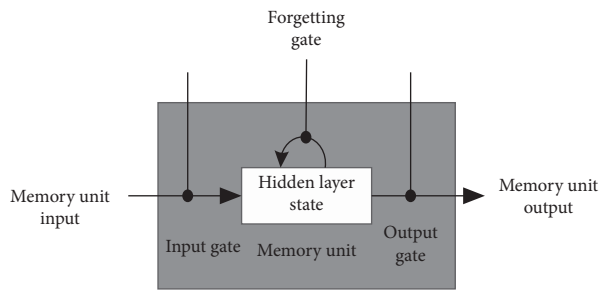

Figure 1: Memory cell structure of long-term and short-term memory network.

$$\begin{cases} \mathfrak{R} = \chi(\aleph \cdot h + \delta \cdot \gamma), \\ \mathfrak{I} = \mathfrak{R} \cdot \delta, \end{cases} \tag{3}$$

where $\mathfrak{R}$ represents the output gate at time t, $\mathfrak{I}$ is the output at time t, $\aleph$ is the weight matrix of the output gate, h is the offset term of the input gate, γ is the offset term of the output gate, χ is the sigmoid activation function, and δ is the weight matrix of the state of the cell. Based on the above process, the financial data characteristics are obtained.

The basic idea of Ma filtering method is: if a stable time series is subject to normal distribution, then the series is strictly stable. So if an ARIMA time series is stable, it may be subject to normal distribution at the same time [31, 32]. To test whether a sequence $\{y_t\}$ is a normal distribution, it is usually judged from its kurtosis. The calculation formula of kurtosis is as follows:

$$\text{kurtosis} = \frac{E\{\{y_t\} - E\{y_t\}\}^4}{\left(E\left\{\{y_t\} - E\{y_t\}^2\right\}^2\right)}. \tag{4}$$

If the kurtosis is 3, the sequence follows the normal distribution, that is, the sequence is low volatility. If the kurtosis is too large or too small, the sequence is either low kurtosis or peak [33, 34], that is, the sequence is high volatility.

The MA filter first separates the low volatility component from the original estimated time series $\{y_t\}$. Suppose this component is represented by y_{tr}:

$$y_{tr} = \frac{1}{m} \sum_{i=t-m+1}^{t} y_i. \tag{5}$$

The components with high volatility are represented by y_{res}:

$$y_{\text{res}} = y_t - y_{tr}. \tag{6}$$

The core idea of nonlinearity of financial data is to extract depth features from the historical data that are helpful to predict the future trend in stock price. Therefore, the nonlinear volatility risk prediction model of financial data is designed and implemented as a network structure of self-trend flow [35, 36]. As shown in Figure 2, the model creatively combines wavelet transform, noise reduction self-encoder, and short- and long-term memory network module, and Wavelet module is used to reduce the noise of basic financial market data.

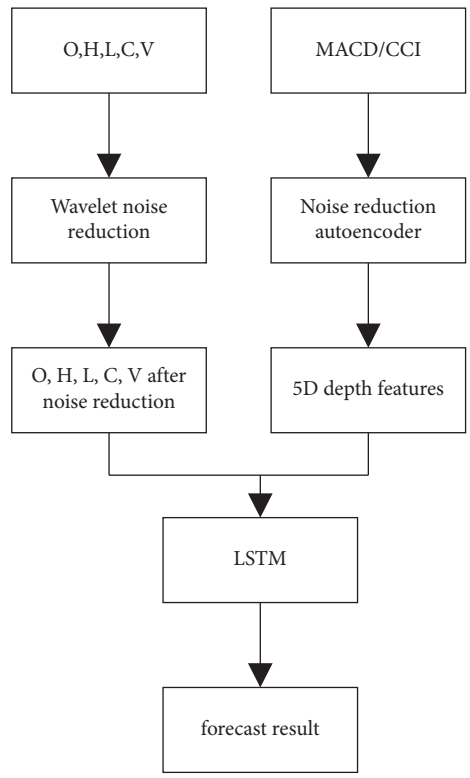

Figure 2: Network model structure.

Financial time series data not only contain high noise, but also generally have the characteristics of nonlinear, nonstationary, and high volatility, which makes the traditional noise reduction methods cannot get better noise reduction effect [37, 38], and the prediction difficulty of financial time series increases. The relevant research results show that wavelet transform technology is able to deal with nonstationary and highly irregular financial time series data, and it can effectively filter out the noise of financial time series data and retain more original information. Therefore, this model uses the wavelet transform module to reduce the noise of the basic financial market data, and more trend information can be obtained after noise reduction. The basic market data of financial data include opening price, peak price, lowest price, closing price, and trading volume (O, H, L, C, V). Through the analysis of historical market data of stock, the historical trend characteristics of stock financial time series are obtained.

Financial time series prediction is seriously affected by noise, so it is necessary to reduce noise before modeling and analyzing. The basic purpose of noise reduction is to remove as much noise information as possible on the basis of preserving the main data characteristics of the original signal. Due to the nonlinear, nonstationary, and high wave characteristics of financial time series data, traditional noise reduction methods cannot effectively remove the noise components [39]. With the continuous development of wavelet transform theory, many researchers apply wavelet denoising technology to financial time series and have achieved relatively ideal denoising effect. For continuous

wavelet transform (CWT), the definition of wavelet transform is as follows:

$$\phi_{\alpha,\tau}(t) = \frac{1}{\sqrt{\alpha}}\phi\left(\frac{t-\tau}{\alpha}\right), \tag{7}$$

where $\phi_{\alpha,\tau}(t)$ is wavelet basis function, and α and τ are scale factor and translation factor, respectively. Wavelet basis functions should meet the wavelet admissibility conditions:

$$C_\phi = \int_0^\infty \frac{|\Phi(\omega)|}{\omega} d\omega < \infty, \tag{8}$$

where $\Phi(\omega)$ is the Fourier transform of the wavelet basis function $\phi(t)$ [40]. If there is a continuous time series $x(t)$ and its square is Lebesgue integral, the continuous wavelet transform of $x(t)$ based on wavelet $\phi(t)$ can be defined as:

$$\mathrm{CWT}_x(\alpha,\tau) = \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\tilde{\phi}\left(\frac{t-\tau}{\alpha}\right)\mathrm{d}t, \tag{9}$$

where $\tilde{\phi}(t)$ is the conjugate complex function of $\phi(t)$. The inverse transform of continuous wavelet transform can be written as follows:

$$x(t) = \frac{1}{C_\phi}\int_{-\infty}^{+\infty}\frac{da}{a^2}\int_{-\infty}^{+\infty}\mathrm{CWT}_x(\alpha,\tau)\phi_{\alpha,\tau}(t)d\tau. \tag{10}$$

Because there is a lot of redundant information in the coefficients of CWT, it is necessary to sample the coefficients reasonably in order to reduce the redundancy. Time series can be decomposed into orthogonal component set and discrete wavelet transform (DWT) will be obtained.

The mother wavelet is used to describe the high-frequency part of the time series [41], while the parent wavelet is used to describe the low-frequency part of the time series:

$$\begin{aligned}\int \varphi(t)\mathrm{d}t &= 1,\\ \int \psi(t)\mathrm{d}t &= 0.\end{aligned} \tag{11}$$

Discrete wavelet transform needs to select the decomposition layer number J according to the actual situation, and the mother wavelet and the father wavelet of each layer are slightly different. The expression of the mother wavelet and the father wavelet of the j layer is as follows:

$$\begin{aligned}\varphi_{j,k}(t) &= 2^{-i/2}\varphi\left(2^{-j}-k\right),\\ \psi_{j,k}(t) &= 2^{-i/2}\psi\left(2^{-j}-k\right),\end{aligned} \tag{12}$$

where j denotes the number of decomposition layers and k denotes the discrete value. Through the discrete wavelet decomposition of $x(t)$ is completed by each mother wavelet and father wavelet, the wavelet coefficients $s_{J,k}$ and $d_{J,k}$ after decomposition can be obtained:

$$\begin{aligned}s_{J,k} &= \int \varphi_{j,k}x(t)\mathrm{d}t,\\ d_{J,k} &= \int \psi_{j,k}x(t)\mathrm{d}t.\end{aligned} \tag{13}$$

Through wavelet coefficients $s_{J,k}$ and $d_{J,k}$, and wavelet basis functions $\varphi(t)$ and $\psi(t)$, inverse transform of discrete wavelet transform can be realized and original signal $x(t)$ can be reconstructed:

$$x(t) = f(t) + e(t). \tag{14}$$

Through the wavelet principal component analysis and noise reduction module and long and short-term memory network (LSTM) module, the nonlinear volatility risk prediction model of financial data is established.

2.2. Nonlinear Volatility Risk Prediction of Financial Data Based on Improved Deep Learning. The challenge of nonlinear volatility risk prediction of financial data lies in the complexity of financial data, and the dynamic time series includes a large number of noise, uncertainty, volatility, and concealment. Therefore, the important task of this section is to extract the nonlinear fluctuation trend from multiple financial data series.

The internal structure between the original data can be obtained by principal component analysis (PCA) [42], and the analysis results have high reliability and objectivity.

PCA transforms a set of related variables $(X_1, X_2, \cdots, X_m)^T$ into a set of uncorrelated variables $(Y_1, Y_2, \cdots, Y_m)^T$ through the orthogonal transformation, which meets the two conditions below:

First:

$$\sum_{i=1}^{m}\mathrm{Var}(X_i) = \sum_{i=1}^{m}\mathrm{Var}\left(Y_j\right), \tag{15}$$

where the variance represents the difference and reflects the amount of information.

Second:

Y_k a linear combination of $X_1, X_2, \cdots, X_m$ and is not related to $Y_1, Y_2, \cdots, Y_{k-1}$. At the same time, Y_1 is the first component with the largest variance and Y_2 is the second principal component with the second largest variance, and so on.

Assume $X = (X_1, X_2, \cdots, X_m)^T$ is m dimensional random vector, whose covariance matrix is:

$$\begin{aligned}C_{m\times m} &= \mathrm{Cov}(X) = \begin{bmatrix} C_{11}\cdots C_{1m}\\ \vdots \\ C_{m1}\cdots C_{mm}\end{bmatrix},\\ C_{ij} &= \begin{cases}\mathrm{Cov}\left(X_i, X_j\right)\\ E\{[X_i - E(X_i)]\}\left[X_j - E\left(X_j\right)\right]\end{cases},\\ C_{ii} &= \mathrm{Var}(X_i).\end{aligned} \tag{16}$$

Through PCA $Y = AX$, the matrix multiplication can be written as

$$\begin{bmatrix} Y_1\\ \vdots\\ Y_m\end{bmatrix} = \begin{bmatrix} a_{11}\cdots a_{1m}\\ \vdots\\ a_{m1}\cdots a_{mm}\end{bmatrix}\begin{bmatrix} X_1\\ \vdots\\ X_m\end{bmatrix}. \tag{17}$$

Three principles should be followed to determine the principal components: the principle of minimum similarity change of group points, the principle of least square and the principle of maximum data variation.

Multivariable prediction problems cannot be solved by traditional statistical methods but can be addressed by neural networks. However, neural network cannot express the relationship between the input and output of the predicted dataset. Therefore, it is also difficult to carry out statistical test on the data calculated by training or explain the results well [43]. In addition, when using neural network to predict, it takes long time to set parameters into repeated tests and select the best result from multiple tests. Moreover, neural network requires more data for prediction and suffers the possibility of convergence to local minimum value. Despite these problems, neural network is expecting to bring a new direction for prediction [44, 45].

Neural network has generalization ability through training and learning [46]. Through training samples, neural network can find the internal law of sample data mapping relationship, rather than simply memorizing sample input, so as to correctly predict the input-output mapping relationship that does not appear [47].

When the generalization ability of neural network is poor, it cannot find the input-output mapping relationship of untrained samples. The structure of neural network and the characteristics of training samples are the main factors determining the generalization ability of neural network [48]. Three main factors are considered when selecting training samples, that is the length of the sample, the representativeness of the sample, and the division way of sample [49].

The output layer of neural network is composed of output neurons, and the input layer and hidden layer of neural network are composed of the remaining neurons. On the basis of the above analysis, combined with the training of reverse neural network, the nonlinear fluctuation trend in financial data is extracted from multiple financial data sequences to achieve the purpose of prediction.

3. Simulation Experiment

Simulation experiments are carried out to validate the effectiveness of the proposed algorithm. The experimental results are compared with the experimental results in reference [16].

The experimental data are collected from 150 typical Internet finance platforms that have been operated continuously from January 2021 to January 2022. The statistics after collection, accounting, and compilation of the samples includes the monthly data of 16 characteristic variables, with a total of 5,000 samples. The characteristic variables include the number of investors (people) X_1, the number of borrowers (people) X_2, the average expected yield (%) X_3, the average borrowing period (month) X_4, the average borrowing period (ten thousand yuan) X_5, the net inflow of funds (ten thousand yuan) X_6, the ratio of the outstanding amount of the top ten investors (%) X_7, the ratio of the outstanding amount of the top ten borrowers (%) X_8, the transaction volume (ten thousand yuan) X_9, the loan scale (number) X_{10}, the time limit (points) X_{11}, the outstanding balance (ten thousand yuan) X_{12}, the average investment amount (ten thousand yuan) X_{13}, the average borrowing amount (ten thousand yuan) X_{14}, the operating time (month) X_{15}, and the business income (ten thousand yuan) X_{16}.

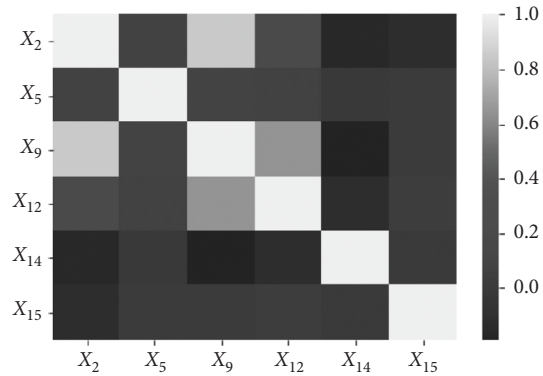

Figure 3: Correlation of financial data characteristics.

Table 1: Prediction error changes of the three algorithms.

Number of test samples	The proposed algorithm Prediction error/(%)	The algorithm in reference (Zhang 2016) Prediction error/(%)	The algorithm in reference (Liu 2016) Prediction error/(%)
1000	0.00	0.10	0.14
2000	0.08	0.09	0.18
3000	0.02	0.11	0.15
4000	0.01	0.15	0.19
5000	0.00	0.07	0.17
6000	0.03	0.08	0.16
7000	0.05	0.12	0.22
8000	0.02	0.10	0.19
9000	0.01	0.15	0.18
1000	0.00	0.13	0.17
1100	0.03	0.14	0.16
1200	0.01	0.16	0.15

In order to verify the validity of the LSTM model proposed in this study, the correlation thermodynamics map will be drawn by using the financial data features extracted by LSTM. As shown in Figure 3, the deeper the color is, the more independent the features are, the weaker the correlation is. Except that the diagonal is autocorrelation, the correlation between X_2 and X_9 is 0.69, and the other features do not have the problem of multiple collinearity. Although the three algorithms obtain different feature subsets, the classification ability of the interaction is more than 80%.

The correlation of the characteristic factors is analyzed, and the index series is used to calculate the contribution degree of each index. According to Figure 3, the factors with higher classification ability are X_9, X_{12}, X_{14}, and X_{15}, which is consistent with the actual situation.

Table 2: Relative error changes of the three algorithms.

Number of test samples	The proposed algorithm Relative error/(%)	The algorithm in reference [11] Relative error/(%)	The algorithm in reference [16] Relative error/(%)
1000	0.02	0.15	0.17
2000	0.00	0.14	0.20
3000	0.03	0.10	0.15
4000	0.01	0.13	0.18
5000	0.04	0.12	0.20
6000	0.02	0.17	0.23
7000	0.01	0.14	0.21
8000	0.03	0.16	0.23
9000	0.04	0.14	0.22
1000	0.06	0.12	0.25
1100	0.03	0.13	0.24
1200	0.02	0.15	0.22

Table 3: Comparison of operation costs.

Time/ (Days)	The proposed algorithm Operation cost/ (ten thousand RMB)	The algorithm in reference [11] Operation cost/ (ten thousand RMB)	The algorithm in reference [16] Operation cost/ (ten thousand RMB)
15	0.85	0.96	1.30
20	0.88	1.05	1.41
25	0.93	1.13	1.56
30	1.02	1.18	1.64
35	1.10	1.21	1.76
40	1.14	1.27	1.87
45	1.18	1.34	1.98
50	1.23	1.39	2.06
55	1.26	1.46	2.20
60	1.30	1.53	2.35
65	1.37	1.59	2.42
70	1.45	1.67	2.50

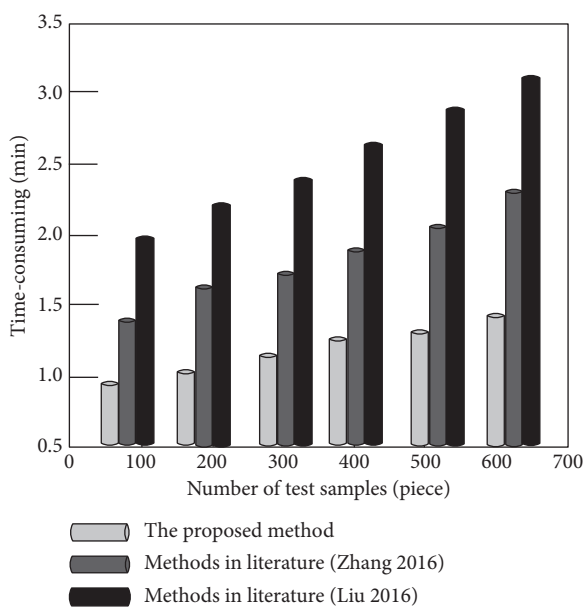

Figure 4: Comparison results of time consumption of three different algorithms.

The prediction error, relative error, time consumption and operation cost are selected as evaluation indexes for simulation test. The prediction effect comparison of three different algorithms is given in Table 1 and Table 2.

Compared with the traditional prediction algorithms, the prediction result of the proposed algorithm is obviously better.

The following experiments compare the time consumption of different algorithms, as shown in Figure 4:

From the experimental data in Figure 4, the proposed algorithm has the lowest time consumption, while the reference algorithm has the second lowest [11].

The operation costs of different algorithms are compared, as shown in Table 3:

The operation cost of the proposed algorithm is significantly lower.

4. Conclusion

Traditional nonlinear volatility risk prediction algorithms of financial data still have a series of problems. To this end, a nonlinear volatility risk prediction algorithm of financial data is proposed based on improved deep learning. Financial data is taken as the research object, and the closing price is set as the prediction target; then a nonlinear volatility risk prediction model of financial data is established through the wavelet principal component analysis (PCA) module and the long-term and short-term memory network (LSTM) module. Experimental results show that the time consumption of the proposed method can be kept within 1.5 min. For 1200 test samples, the average error of data risk prediction and relative error is 0.0217% and 0.2583%, respectively, showing that the error of research method is lower than that of reference method. The average cost of the research method is 114.25 million yuan, which is significantly lower than other existing algorithms.

Future research will focus on the following aspects:

(1) The prediction model needs to be improved, in which the denoising effect is not very ideal and it will be further improved in the future.

(2) The multiscale data input can be introduced into the prediction model, so as to achieve better prediction performance.

(3) Investors can invest capital in multiple markets, and the next step is to establish a cross market prediction research model.

(4) In the follow-up study, macroeconomic indicators such as GDP may be introduced to analyze the stock index. In addition, some technical analysis indexes, such as relative strength index and moving average, can be used as input variables to reduce the dimension of PCA algorithm, so as to improve the prediction accuracy and shorten the training time.

Although this study has achieved good results, there are still some limitations. How to determine the characteristic

factors reasonably and apply them to the model design is an important basis for the big data financial risk early warning method to deal with high dimensional data. In the future research, we need to extract multidimensional early warning factors and fuse coevolution mechanism for early warning analysis, which can effectively take advantage of information resources and improve convergence speed and accuracy.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

It is declared by the authors that this article is free of conflicts of interest.

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Research Article

Tail Risk in the Chinese Vegetable Oil Market: Based on the EGAS-EVT Model

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This paper uses extreme value theory and exponential generalised autoregressive score models to estimate the tail extremes of financial return series. The peak-over-threshold method based on the generalised pareto distribution is combined with the EGAS models and the nonparametric quantile method is used to determine the thresholds in the POT method, which is used to calculate the value-at-risk of financial markets and to perform backtesting. The empirical analysis was conducted on the soybean oil, rapeseed oil, and palm oil futures indices in the Chinese futures market. The study demonstrated that the EGAS-POT models based on nonparametric quantile thresholds can effectively characterise tail risk and provide a feasible measure of risk for investors.

1. Introduction

In recent years, China's economy has made remarkable achievements. At the same time, as the Chinese futures market gradually integrated with the international futures market. In 2020, 6.153 billion lots and 437.53 trillion yuan were traded in China's futures market, accounting for 13.2% of the total volume in the global futures market. Palm oil, soybean oil, and rapeseed oil on China's futures market will rank second, fourth, and ninth, respectively, in the global trading volume of agricultural futures and options. Chinese vegetable oil futures is one of the most widely used varieties in the Chinese market. Moreover, Chinese vegetable oil futures are typical in agricultural futures market. There is a substitute or complementary relationship among all varieties, and it is closely related to spot price. In addition, the price fluctuation of vegetable oils, oilseed, and oilseed meal has a wide range of influence, which has direct or indirect impact on the living consumption of residents, processing of food enterprises, and production of livestock enterprises. Since soybean futures were listed in 1993, oil and oil futures have gradually realized the integration of upstream and downstream of the industrial chain and the diversification of derivatives, such as futures and options. By introducing foreign traders to participate in the trading of palm oil futures and options and other kinds of instruments, they can hedge and avoid risks to a certain extent. China oil futures price is also a leading indicator to monitor the price fluctuation of oil agricultural products and reflect the change of consumer price level. The price fluctuation not only has the transmission mechanism from futures to spot market but also has the cross-market and cross-period relationship. In the context of accelerating the financialisation of agricultural products and preventing systemic financial risks, the role of agricultural futures market in managing price risks is more prominent. Therefore, it is of great theoretical and practical significance to study the risk of vegetable oil futures.

In the context of globalisation, risk measurement has always been an important part of financial risk management and investors and regulators have studied quantitative tools for financial risk, such as value-at-risk [1] (VaR), for this purpose. However, as extreme events have had a huge

impact on financial markets, the volatility in international financial markets has increased, the risk of a global economic downturn is growing, and uncertainty about the outlook has increased dramatically. The tails of traditional metrics describing the distribution of returns are underperforming.

The behaviour of the tails of financial risk has been assessed by many scholars. McNeil [2], Jondeau and Rockinger [3], and Da Silva and Mendez [4] showed that the tails of returns on asset returns have extreme values and do not follow a normal distribution and that their empirical distribution is characterised by spikes and thick tails. Therefore, classical parametric methods based on the assumption of a normal distribution are not suitable for estimating risk in financial markets. One of the ideal alternative parametric methods is extreme value theory (EVT), and methods based on EVT can be used on the basis of VaR. Embrechts [5] discusses the application of EVT to risk modelling. Manfred Gilli and Evis Kellezi [6] apply EVT to measure tail risk in six stock market indices, The results show that extreme value theory is effective for estimating extreme events in financial markets and that the POT method allows better use of information in the data sample to understand the details of financial market data. McNeil [7] showed that direct application of EVT can overestimate or underestimate VaR as the financial asset return series do not satisfy the assumption of independent homogeneous distribution, and there is heteroskedasticity. Therefore, the original income sequence needs to be processed.

Starting from Engle's autoregressive conditional heteroskedasticity [8] (ARCH) model. The problem of constant variance of time series variables in traditional econometrics is solved. More models have been developed to model volatility, such as the generalised autoregressive conditional heteroskedasticity [9] (GARCH) model, the exponential generalised autoregressive conditional heteroskedasticity [10] (EGARCH) model, and the asymmetric power generalised autoregressive conditional heteroskedasticity [11] (APARCH) model. These models perfectly interpret the volatility characteristics of time series in financial markets, such as asymmetry and leverage. As financial markets become more complex. Creal, Koopman, and Lucas [12] creatively proposed a unified framework for modelling time-varying parameters, namely the generalised autoregressive score (GAS) models, which provides a new option for modelling financial asset return volatility. Nortey et al. [13] modelled the extreme values of stock index volatility in Ghana by the autocorrelation of the return series was corrected and the conditional heteroskedasticity in the presence of collections. Applying EVT to fit the tails of daily stock return data for Ghana, the study showed that among the methods used to estimate the parameters, the maximum likelihood estimation (MLE) method provides more accurate estimates. Taking the top 10 sector indices of the SSE as an example, Ping [14] developed a GAS volatility model to predict and compare the out-of-sample VaR forecasting effects of the model. The study showed that the GAS volatility model for time-varying volatility modelling can effectively use the valid information of the distribution, and VaR performs better. To analyse the correlation between different types in the financial market, Rongda and Jianjun [15] developed a multivariate GAS model to analyse the interaction between the dependence balances and volatility between the prices of crude oil and gold, and the results show that the predictive power of volatility and correlation in the multivariate GAS model outperforms the DCC-GARCH model. Lazar and Xiaohan [16] introduced intraday information into the GAS model in quantile regression setting to estimate risk. The results show that the GAS model, augmented by the implemented volatility metric, consistently outperforms other models across all indices and various probability levels.

Traditional time-series models, such as AR model, MA model and GARCH family model, were mostly used in previous studies. In addition, they tend to predict the return series or measure the risk of the return series of stock index. There are few researches on the risk measure of the return series of agricultural futures and futures index in the financial market. In this paper, the time-varying parameters based on the score function are introduced into the EGARCH model for the futures index of Chinese vegetable oils and fats, and the most suitable residual distribution is selected. A nonparametric method is proposed to select the threshold value for the extreme value of the filtered standardized residual sequence, and the EGAS-POT model is established by combining the extreme value theory. Compared with the traditional threshold selection method, the utility of the model in risk measurement is investigated and tested back. Based on the empirical analysis results, some reasonable suggestions are put forward for the risk management of vegetable oil futures in China.

2. Materials and Methods

2.1. EGAS Volatility Model. The GAS model also goes by the name of dynamic conditional score (DCS) model, Score driven (SD) model, or dynamic score (DySco) model, is a time-varying volatile parametric models driven by observations that allows the model parameters to vary as the score function of the log-likelihood function changes. The dynamic behaviour of the time-series process is portrayed through the dynamics of the parametric variables leading to the variables and exogenous variables. The EGAS model, on the contrary, builds on the GAS model using the logarithm of the conditional variance instead of the conditional variance, allowing for asymmetries in positive and negative asset returns on volatility, thus allowing the dynamics of the impact of positive and negative returns on volatility to be captured effectively.

Assuming that y_t is the financial time-series observation, σ_t is the time-varying conditional y standard deviation, which represents the volatility of the time-series data, and F^{t-1} is the information set at moment $t-1$, then the observation y_t probability density function is as follows:

$$p\left(y_t|\sigma_t, F^{t-1}\right). \tag{1}$$

Then the expression for the EGAS model based on time-varying volatile is as follows:

$$\begin{cases} y_t = \mu + \sigma_t z_t, \\ \ln \sigma_{t+1}^2 = \omega + \sum_{i=1}^{p} A_i s_t + \sum_{j=1}^{q} B_i \ln \sigma_t^2, \nabla_t = \dfrac{\partial \ln \ p\left(y_t|\sigma_t, F^{t-1}\right)}{\partial \ln \ s_t}, \end{cases} \begin{matrix} s_t = S_{t-1}\nabla_t, \\ S_t = I_t^{-\gamma}, \end{matrix} \quad I_t = \left[\nabla_t \nabla_t'\right]. \tag{2}$$

where when $t = 1$, σ_1 is the unconditional standard deviation, z_t is the standardized residual series, A_i and B_i $(i = 1, 2, \ldots, p,\ j = 1, 2, \ldots, q)$ are time-varying coefficient matrices, reflecting the time-varying nature of the fluctuations and the aggregation and mean recovery of the fluctuations, respectively, usually p and q can be taken as 1. ω is the constant vector; I_t is the information matrix; S_t is the deflation matrix; in general, γ takes 0, at this time; S_t is the deflation matrix is the unit deflation matrix; ∇_t is the score function corresponding to σ_t, is the core driving term of the EGAS fluctuation model.

When the standardized residuals z_t obey a different distribution, the expression for the score function changes as well. For financial time series, the distributions often assumed are: the Gaussian (Normal) distribution (N), the standard student T distribution (ST), the generalised error distribution (GED), and the skewed student T distribution (SKST), where the probability density of the skewed student T distribution is as follows:

$$f(z) = bc\left[1 + \frac{1}{v-2}\left(\frac{bz + a}{1 + \operatorname{sgn}(bz + a)l}\right)^2\right]^{-v+1/2}, \tag{3}$$

where $c = 1/[\sqrt{v-2}\,B(1/2, v/2)]$, $a = 4\lambda c(v-2)/(v-1)$, $b^2 = 1 + 3\lambda^2 - a^2$, $B(\cdot)$ is the beta function, $\operatorname{sgn}(\cdot)$ is the symbolic function, and z is the variable with the mean value of 0 and the variance of 1. Parameter v represents the kurtosis of the skew t distribution. When v is smaller, the kurtosis is larger, and the thick tail of the spike is more obvious. λ is an asymmetric coefficient, indicating the skewness of the skew t distribution. If $\lambda > 0$, the distribution is right, and if $\lambda < 0$, the distribution is left. The skew t distribution includes normal distribution, skew normal distribution, and t distribution. When the parameter $v \longrightarrow \infty$ and $\lambda = 0$, the distribution is normal distribution. When parameter $v \longrightarrow \infty$. At this time, the distribution is skew normal distribution. When the parameter $\lambda = 0$, the distribution is t.

When the standardized residuals obey SKST, the score function is as follows:

$$\nabla_t = \frac{\partial \ln \ p\left(y_t|\sigma_t, F^{t-1}\right)}{\partial \ln \ \sigma_t} = \frac{bz_t(v+1)(bz_t + a)}{(bz_t + a)^2 + v[1 + \operatorname{sgn}(bz_t + a)\lambda]^2} - 1. \tag{4}$$

As can be seen from the score function, the skewness parameter v and the kurtosis parameter λ determine the value of the score function, and as the value of v increases, the score function becomes more sensitive to extreme values; the skewness parameter λ reflects the sensitivity of the score function to shocks on the left side, when the distribution is left-skewed, the score is relatively more sensitive to shocks on the right side; when the distribution is right-skewed, the score is relatively more sensitive to shocks on the left side; when the distribution is symmetrical, the response of the score to shocks on both sides is symmetric.

2.2. Extreme Value Theory. Extreme value theory was introduced by Gnedenk [17]. Also known as the law of small numbers is primarily concerned with the prediction of rare events. The theory aims to investigate the distribution of the extremes of a sequence, using the generalised pareto distribution or generalised extreme value distribution (GEV) to approximate the tail distribution of losses. First applied in hydrology, seismology, and climatology, it is commonly used to analyse probabilistic rare cases. With the increasing refinement of the theory, EVT research has been applied to science and technology, engineering and other fields, with Longin [18] pioneering the use of EVT in risk management with good results. In financial engineering, for the tail characteristics of risk loss distribution, it is usually used to analyse events with rare probability. It can rely on a small amount of sample data to obtain the change of extreme value in the overall distribution when the overall distribution is unknown and has the ability to estimate beyond the sample data.

There are two methods for the application of extreme value theory: Block maxima (BM) method and peak-over-threshold (POT) method, as the use of the BM method leads to the absence of extreme data in the block and the loss of extremely valuable extreme information. This paper uses the POT method, which is more widely used in practice. Clément Dombry and Ana Ferreira [19] show that the POT method is preferable when considering MLE, and the estimation results are more convincing for extreme data values.

Assume that the data of the random variable sequence is $x_1, x_2, \ldots, x_n$ is independently and identically distributed, and the distribution function of the random variable is $F(x)$, let x_m be the maximum value of the random variable sequence data, by setting the threshold value $u\,(u < x_m)$, and all the observed data above this threshold value form a data group $\{Z_i\}$, with this data group as the object of modelling, such that $K_i = Z_i - u$, then we have

$$F_u(k) = P(Z - u \le k | X > u), \quad k \ge 0. \tag{5}$$

The derivation of the conditional probability formula leads to the following:

$$\begin{aligned} F_u(k) &= \frac{F(u+k) - F(u)}{1 - F(u)} \\ &= \frac{F(Z) - F(u)}{1 - F(u)} \Rightarrow F(Z) \\ &= F_u(k)[1 - F(u)] + F(u). \end{aligned} \tag{6}$$

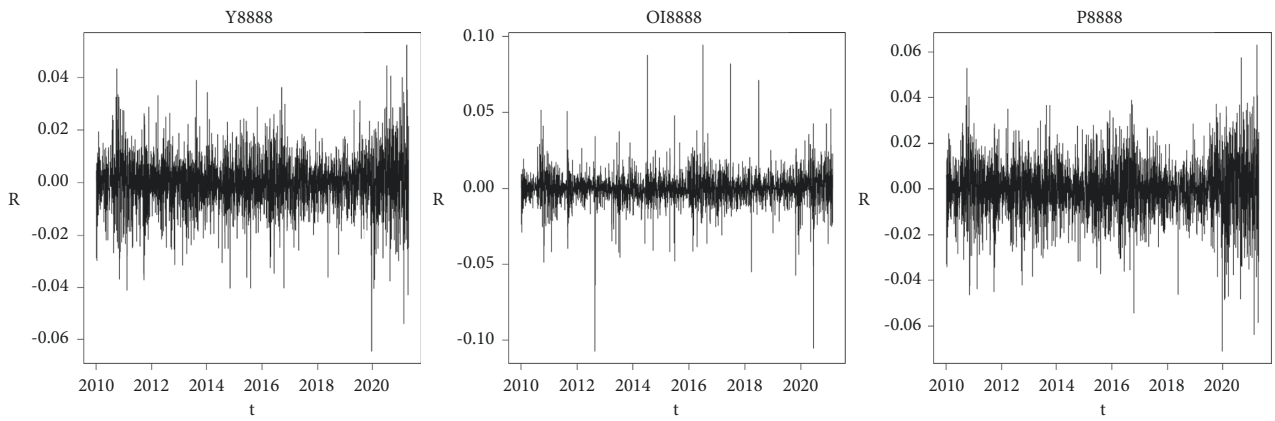

Figure 1: Daily returns trend.

Table 1: Daily returns observations descriptive statistics.

Statistical characteristics	Soybean oil	Rapeseed oil	Palm oil
Sample size	2767	2728	2767
Minimum value	−0.06447	−0.10728	−0.07128
Maximum value	0.05254	0.094483	0.06311
Mean value	1.922*e*-005	7.0085*e*-005	9.4054*e*-006
Standard deviation	0.010503	0.010719	0.012617
Skewness	−0.17887	−0.21697	−0.20044
Super kurtosis	2.1892	15.5152	1.9282

When the threshold u is taken to be relatively high, the suprathreshold distribution will converge to the GPD. The GPD expression is the distribution function $F_u(y)$ approximating the $G'_{\xi,\eta}(y)$ generalised Pareto distribution.

$$\underset{u \longrightarrow \infty}{F_u(k)} \approx G'_{\xi,\eta}(k) = \begin{cases} 1 - \left(1 + \dfrac{\xi}{\eta} y\right)^{-1/\xi}, & \xi \neq 0, \\ 1 - \eta^{-k/\eta}, & \xi = 0, \end{cases} \tag{7}$$

where ξ and η are the shape and scale parameters, respectively. When $\xi \geq 0$, $y \geq 0$, indicating a thick tail of the distribution function, and the presence of extreme values; when $\xi < 0$, $y \in [0, -\xi/\eta]$. The probability density function of the GPD is known, and hence the log likelihood function of a sequence of random variables known to obey an independent distribution:

Table 2: Jarque-Bera test for daily returns.

	X-squared	P value
Soybean oil	567.31	6.4547*e*−124
Rapeseed oil	27,382.00	0
Palm oil	447.19	7.8144*e*−98

$$L(\xi, \eta | k) = \begin{cases} -n \ln \eta - \left(1 + \dfrac{1}{\eta} k\right) \displaystyle\sum_{i=1}^{n} \ln\left(1 + \dfrac{\eta}{\xi} k_i\right), & \xi \neq 0, \\ -n \ln \eta - \dfrac{1}{\eta} \displaystyle\sum_{i=1}^{n} k_i, & \xi = 0. \end{cases} \tag{8}$$

When u is determined, the estimates of ξ and η are obtained by MLE according to equation (8), and the shape parameter ξ reflects the tail of the distribution. At the same time, the number of observations of the random variable series data that exceed the threshold u data can be obtained, denoted as N_u, and the new expression can be obtained by replacing the value of $F(u)$ with the frequency according to equation (6):

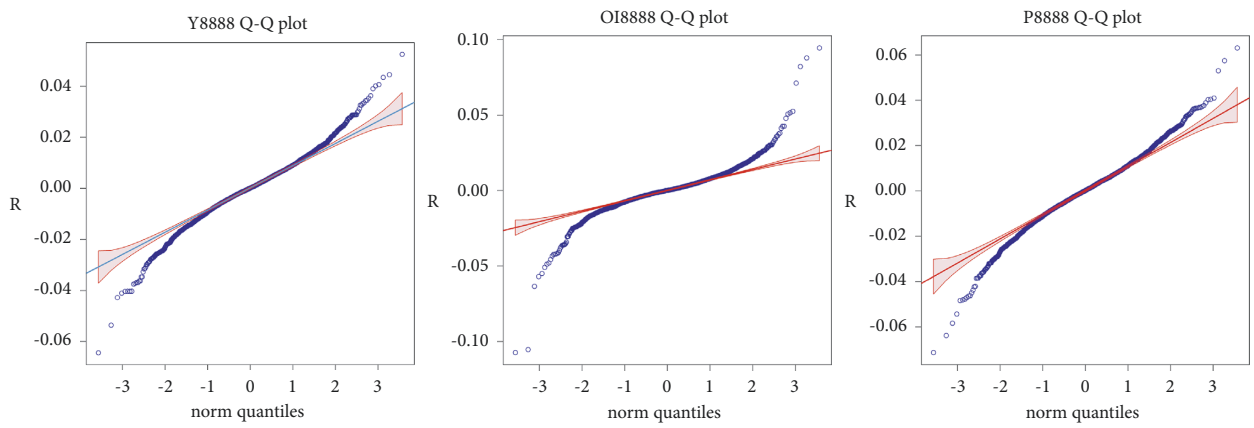

Figure 2: Normal Q-Q plots of daily returns.

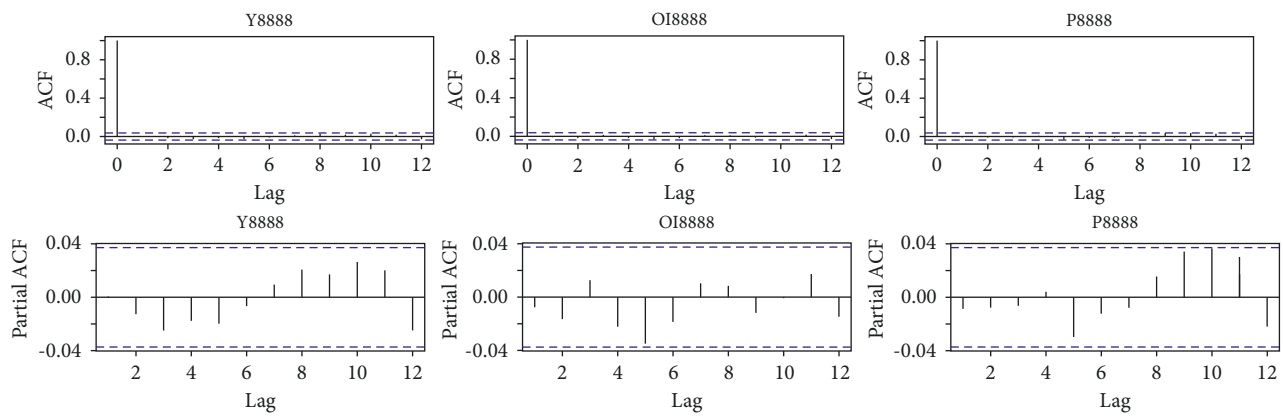

Figure 3: Autocorrelation and partial autocorrelation of daily returns.

$$F_u(k)[1-F(u)]+F(u)=\begin{cases}\dfrac{N_u}{N}\left\{1-\left[1+\dfrac{\xi}{\eta}(z-u)^{-1/\xi}\right]\right\}+\left(1-\dfrac{N_u}{N}\right),\\[2ex] \dfrac{N_u}{N}\left[1-\eta^{-(z-u)/\eta}\right]+\left(1-\dfrac{N_u}{N}\right),\end{cases}$$
$$=\begin{cases}1-\left[1+\dfrac{\xi}{\eta}(z-u)\right]^{-1/\xi}, & \xi\neq 0,\\[2ex] 1-\dfrac{N_u}{N}\eta^{-(z-u)/\eta}, & \xi=0.\end{cases} \tag{9}$$

2.3. VaR Estimation Based on the POT Method. VaR is the maximum possible loss to an investor owning a single asset or portfolio of assets at a certain confidence level p (99%, 95%) and holding period. Its essence is to calculate the tail quantile of the yield distribution, where the long VaR corresponds to the lower tail quantile of the yield distribution and the short VaR corresponds to the upper tail quantile of the yield distribution. The expression of VaR_p is

$$VaR_p=-\inf\{|x|f(X\leq x)>(1-p)\}. \tag{10}$$

Taking equation (9) into equation (10) gives the following:

$$VaR_p = \begin{cases} u - \frac{\eta}{\xi}\left[1 - [-n\ln(1-p)]^{-\xi}\right], & \xi \neq 0, \\ u - \eta\ln[-n\ln(1-p)], & \xi = 0. \end{cases} \quad (11)$$

3. Empirical Analysis

3.1. Data Analysis. The empirical part uses the Chinese futures market Soybean oil (Y8888), Rapeseed oil (OI8888), and Palm oil (P8888) futures indices as raw data (data source: Flush iFinD), with the sample space selected from 4 January 2010 to 31 May 2021, and the first-order difference of the logarithm of the daily closing price is used as the daily log return for ease of processing, that is, $R_t = LnP_t - LnP_{t-1}$, where P_t denotes the closing price on day t and P_{t-1} denotes the closing price on day $t-1$. Figure 1 shows a graph of the daily return series.

Descriptive statistics for the daily return series are shown in Table 1.

As shown in Table 1, from the description of daily logarithmic returns, the average returns of soybean oil, rapeseed oil, and palm oil futures are all near 0, with a range of 0.117006, 0.201763, and 0.134392, respectively. The excess kurtosis coefficient is greater than 0, that is, the logarithmic rate of return series has a peak. The skewness is less than 0, indicating that there are different degrees of left skewness, indicating that there are more huge falls in the market than huge rises, that is, there is a negative skewness vegetable oil futures all exhibit a left-skewed and spiky distribution that does not obey a normal distribution. This is the same result as Balaban's [20] study on the distribution characteristics of daily stock returns and their asymmetry. The test used to test the daily returns for smoothness is the Jarque-Bera [21] test, and the results are shown in Table 2. The original hypothesis is rejected because the significance is much less than the critical value of its significance level of 1%, and the series does not have a unit root, and is a smooth series.

In order to further test the distribution characteristics of the sample series, Figure 2: normal Q-Q plots of daily returns was described. The scattered points on the log-return normal Q-Q plots were curved at both ends and distributed outside the 95% confidence level interval of the normal distribution, indicating that the distribution of log-return is thick-tailed. To sum up, the original sample sequence follows the distribution with sharp peak and thick tail deviating to the left, so the predicted results of VaR calculation method based on normal distribution are too conservative.

Second, part of the efficiency of financial markets also reflects the general autocorrelation between raw returns, so using metrics directly is not feasible. Figure 3: ACF plot shows that there is no autocorrelation in the daily return series, and the autoregressive conditional heteroskedasticity test on the return residual series shows that there is a strong ARCH effect in the residual series through the ARCH-LM test. The POT method requires the sequence of random variables to meet the requirement of independent identical distribution, so for the original data with volatility aggregation and leverage effect, so the volatility model needs to be constructed to filter the return series, and the residual series of each set of returns obeying independent identical distribution is found.

Table 3: EGAS (1,1) model AIC and SC estimation results.

	Assumed distribution	AIC	SC
Soybean oil	N	−6.3496	−6.3498
	ST	−6.3562	−6.3937<
	GED	−6.3994	−6.3908
	SKST	−6.4038<	−6.3931
Rapeseed oil	N	−6.2403	−6.2338
	ST	−6.6442<	−6.6355<
	GED	−6.620	−6.6121
	SKST	−6.6436	−6.6327
Palm oil	N	−6.0132	−6.0068
	ST	−6.0457	−6.0372<
	GED	−6.0421	−6.0335
	SKST	−6.0472<	−6.0365

Table 4: Results of parameter estimation for EGAS (1,1)-SKST model.

	A_1	B_1	λ	ν
Soybean oil	0.051642	0.990683	−0.061800	6.800666
Rapeseed oil	0.118198	0.97477	−0.010878	3.297259
Palm oil	0.047381	0.994420	−0.063079	7.926744

Table 5: Thresholds **u** selection.

	Soybean oil	Rapeseed oil	Palm oil
Long position u	−1.279089	−1.070747	−1.521152
Short position u	1.219153	1.048097	1.188821

Table 6: GPD fitting parameters.

	Long position		Short position	
	ξ	η	ξ	η
Soybean oil	0.5710	0.0528	0.2650	0.5560
Rapeseed oil	0.4980	0.3090	0.0386	0.7820
Palm oil	0.0232	0.8240	0.0269	0.5500

3.2. Model Parameter Estimation. In this study, the EGAS (1,1) model was chosen to filter the data for each set of return series and to compare the fit of the model under various hypothetical distributions according to the AIC criterion and the SC criterion. The AIC and SC estimation results of the model are shown in Table 3:

As can be seen from Table 3, the hypothetical distribution with skewed, spiky and thick-tailed characteristics is significantly better than the symmetric hypothetical distribution, and the hypothetical distribution of raw returns is chosen as SKST.

According to the parameter estimation results in Table 4, the parameter A_1 was significantly greater than 0, indicating that the return rate series had obvious time-varying

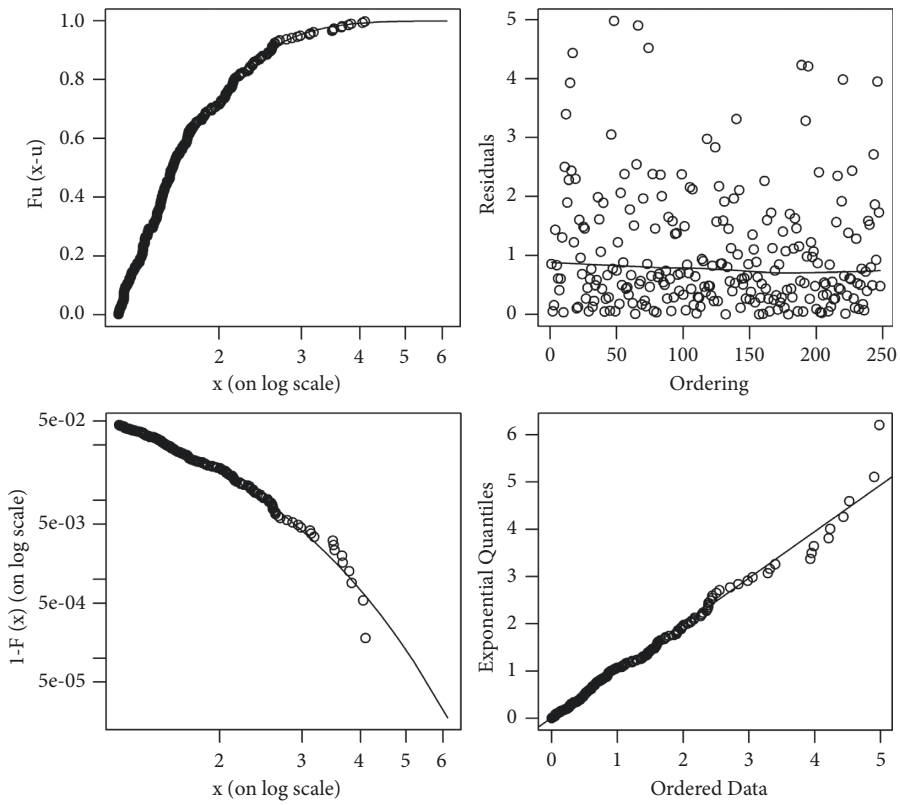

Figure 4: Soybean oil positive returns GPD fitted diagnostic plots.

fluctuation characteristics. Parameter B_1 is close to 1, which means that the return rate series has a strong agglomeration, $A_1 < B_1$, which means that the unexpected news impacts the fluctuation of return, and $A_1 > 0$, it proves that this kind of shock is positive, that is, the occurrence of fluctuation is usually followed by a larger fluctuation in the later period. In terms of distribution parameters, the palm oil futures parameter ν is larger, reflecting more extreme risk exposure in historical data.

3.3. The POT Method. The residual series obtained by constructing the EGAS (1,1)-SKST model satisfies the POT method requirements such that the residual series $\{X_t\} = \{z_t\}$ and the distribution function is fitted with GPD model for data above the threshold extremes. In performing model estimation, the upper and lower tail thresholds of the residual series are first determined. Caeiro [22] used different methods for the selection of the thresholds a comparative analysis was carried out.

In this paper, we adopt a novel nonparametric method for selecting the threshold u. Applying Grevenko's theorem [23], the empirical distribution function is related to the overall distribution function, thereby improving the accuracy of the quantile of the original data series.

Step 1. If the number of data in the residual series is N, let the parameter $M = 100$, extract 100 data item by item in the residual series in time order, select the 2nd to 101 data for the 2nd time, ..., select the ith to $i + 99$ data for the ith time, and so on, to obtain $(N - M + 1)$ data.

Step 2. Based on the confidence level α, the quantile values of each group of data were calculated separately using the historical simulation method combined with the principle of Mouchel [24] and through Holger Drees [25] in a comparative study of random and deterministic thresholds, so that $\alpha = 10\%$ to obtain $(N - M + 1)$ quantile values.

Step 3. The average of the selected quantiles is noted as s. The value closest to s is found in the new interest sequence, which is noted as the threshold value u, and u is used as the threshold value in the POT method.

The nonparametric method not only effectively avoids the subjective judgement of thresholds based on image methods that lead to over or improper fitting, but for the value of α avoids the situation in the POT method where extreme values are piled up leading to too large a choice of thresholds and a small sample of extreme value data. The results based on the nonparametric threshold selection are shown in Table 5.

The results of the nonparametric method of fitting are shown in Table 6.

In order to test the fitting effect of the POT method, we further give Figures 4 to 9 GPD fitting diagnostic plots for the fitting of the residual series. Observe that the data points in the graph are concentrated in each distribution curve except for individual data, proving that the POT method fits

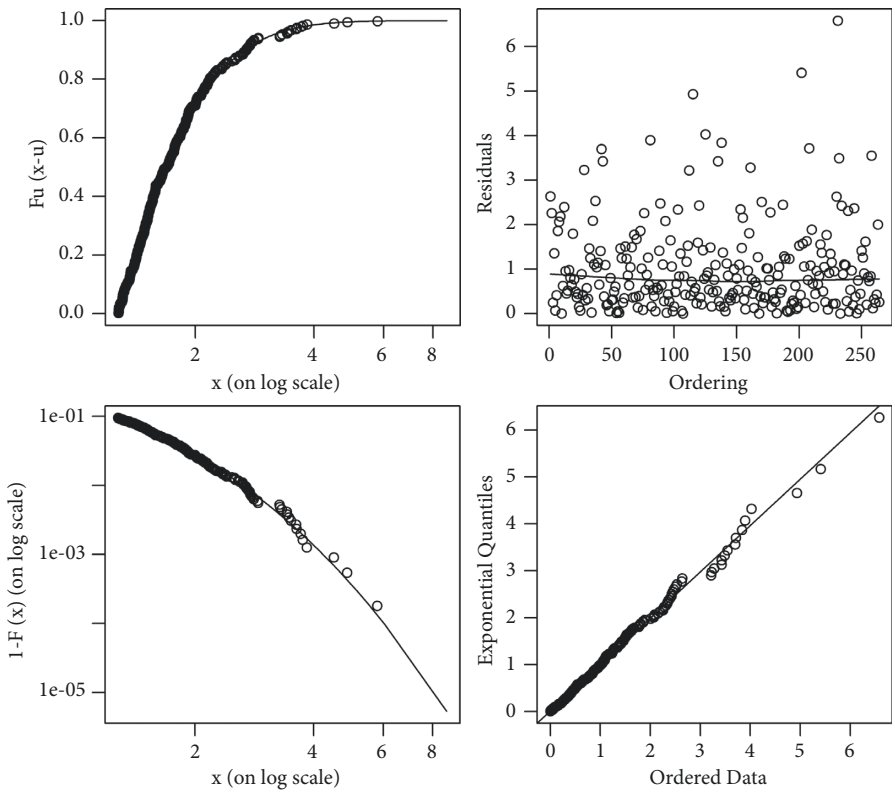

Figure 5: Soybean oil negative returns GPD fitted diagnostic plots.

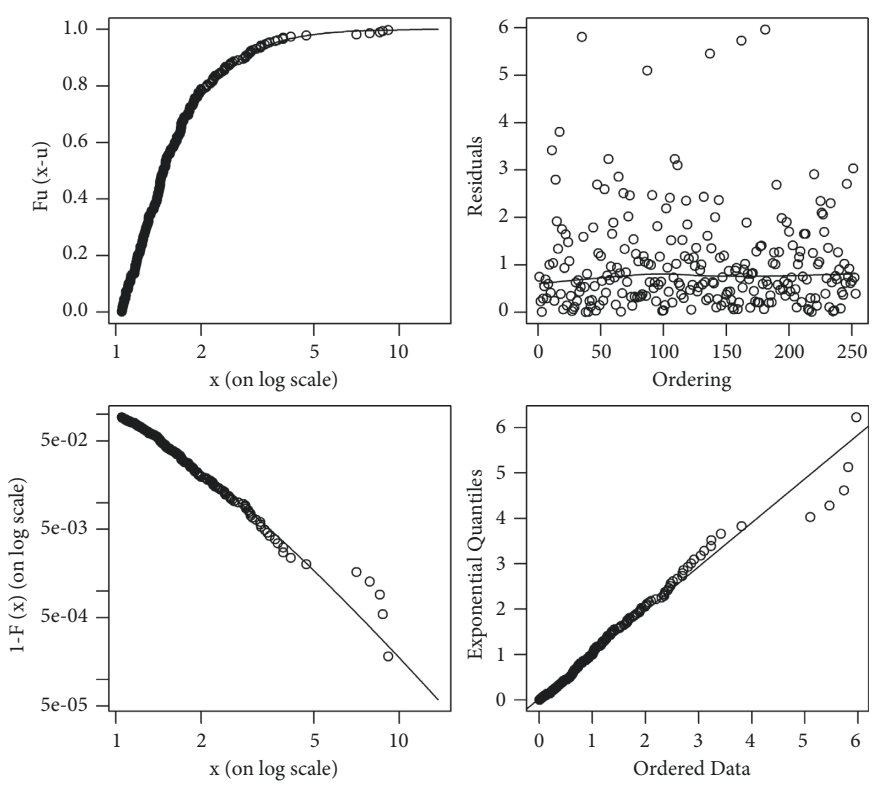

Figure 6: Rapeseed oil positive returns GPD fitted diagnostic plots.

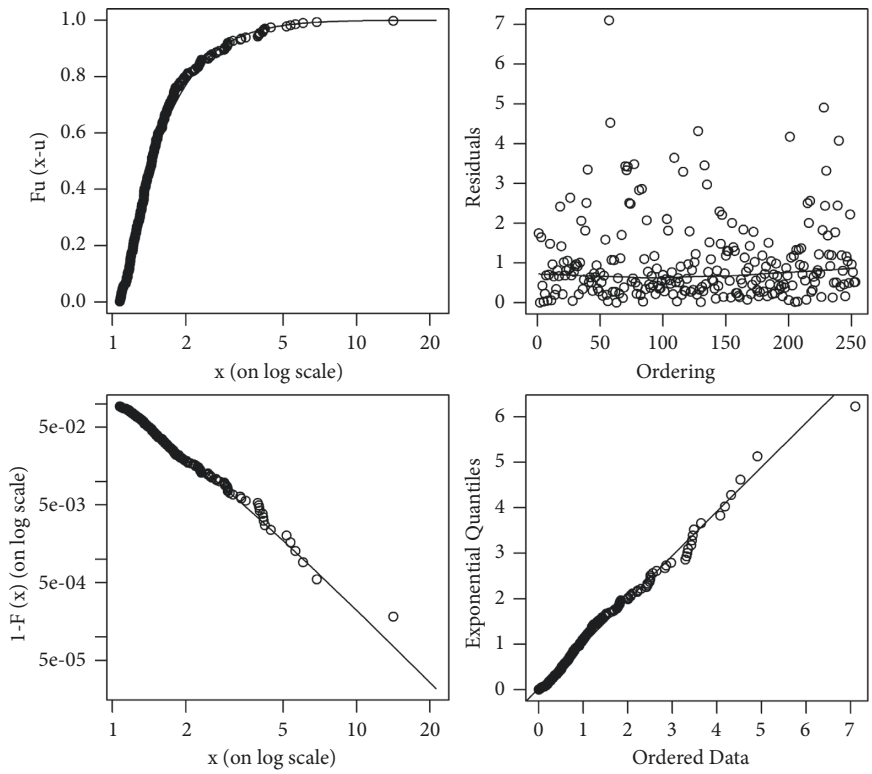

Figure 7: Rapeseed oil negative returns GPD fitted diagnostic plots.

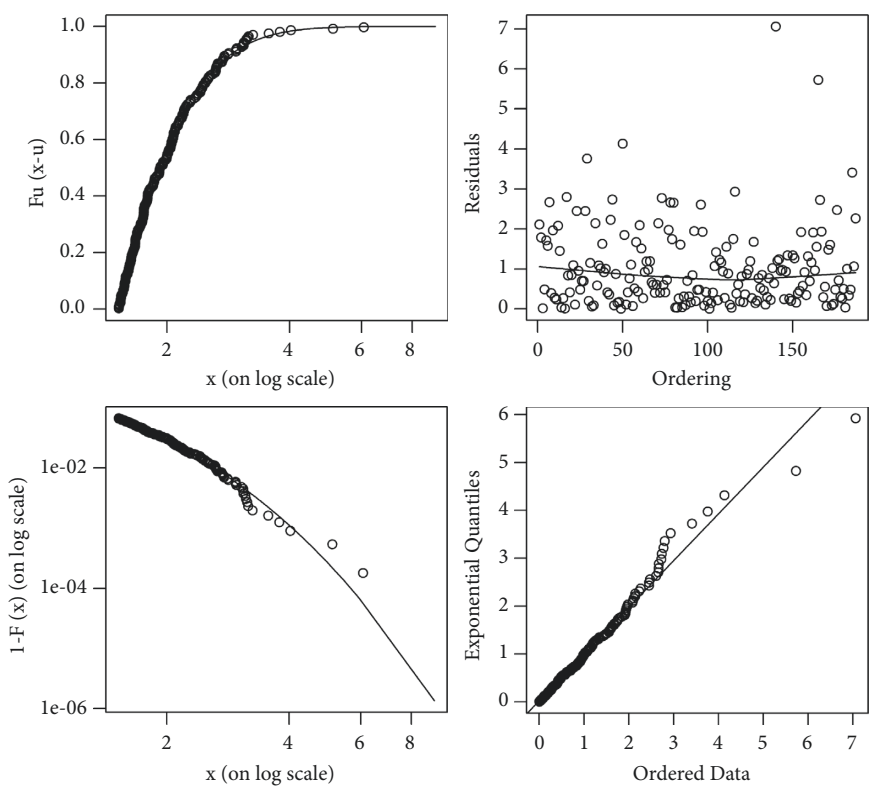

Figure 8: Palm oil positive returns GPD fitted diagnostic plots.

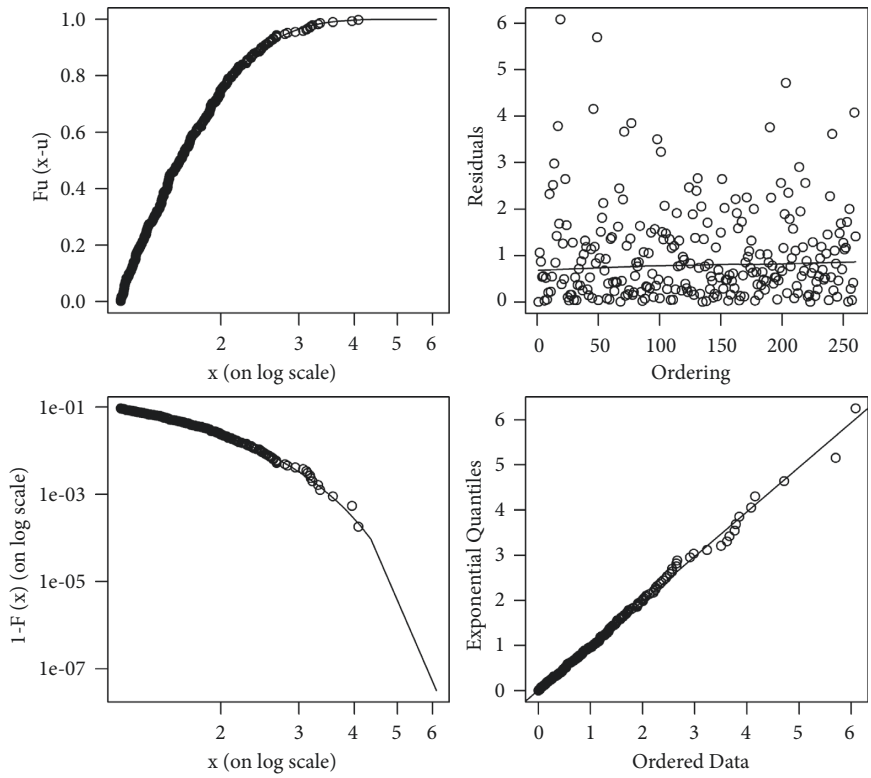

Figure 9: Palm oil negative returns GPD fitted diagnostic plots.

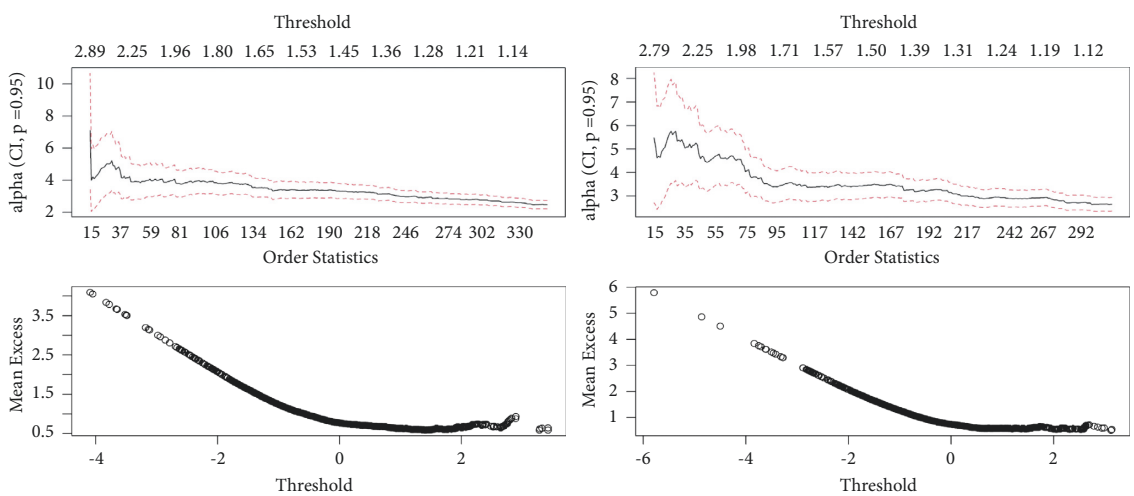

Figure 10: Soybean oil-Hill plots and the MEF plots. The top is the Hill plot, the bottom is the MEF plot, the left is the negative returns plots and the right is the positive returns plots.

the extreme data of the new coupon series well and can accurately reflect the tail characteristics of the true loss distribution of the extreme risk of the returns series.

In order to compare the validity of the nonparametric method of threshold selection, the Hill estimator [26] and the mean excess function [27] (MEF) were used to estimate the VaR values by Figure 10 selecting the threshold u_1 and performing a comparative analysis. The Hill plots Figure 10 and MEF plots are shown in Figures 10 to 12.

The thresholds u_1 were selected by observing Hill plots and MEF plots, and the results of the threshold selection are shown in Table 7.

Define the nonparametric method to select the threshold value of VaR is VaRn, Hill estimation method and MEF method to select the threshold value of VaR is VaRm, respectively, at the confidence level p of 99% and 95% of the VaR value, The estimation results are shown in Tables 8 and 9.

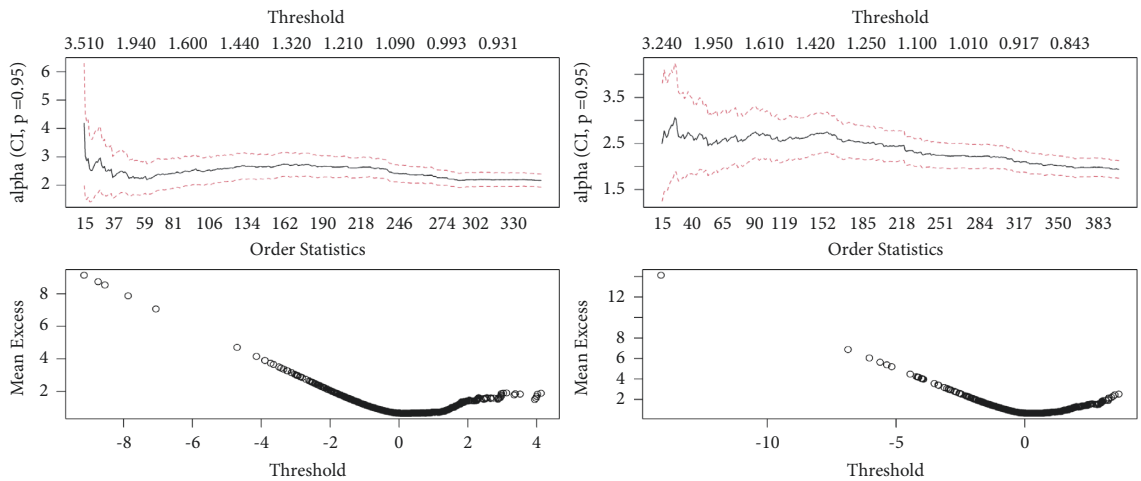

Figure 11: Rapeseed oil-Hill plots and the MEF plots.

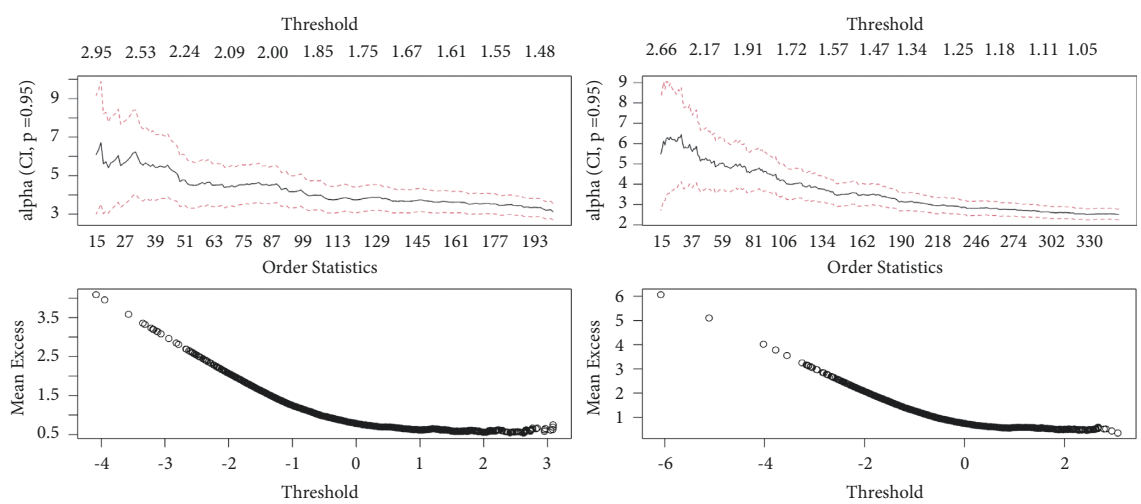

Figure 12: Palm oil-Hill plots and the MEF plots.

Table 7: Thresholds $\mathbf{u}_1$ selection.

	Soybean oil	Rapeseed oil	Palm oil
Long position u_1	−1.280722	−1.007843	−1.590512
Short position u_1	1.213788	1.033504	1.161942

Table 8: VaRn estimation results.

	p	Long position $\mathrm{VaR_n}$	Short position $\mathrm{VaR_n}$
Soybean oil	95%	−1.640087	1.556682
	99%	−2.664474	2.502442
Rapeseed oil	95%	−1.411081	1.421339
	99%	−2.677870	2.762528
Palm oil	95%	−2.063909	2.015324
	99%	−3.435836	3.185844

3.4. VaR Backtesting. The test for VaR takes the Kupiec test [28], which is a very widely used method of posterior analysis, by constructing a likelihood ratio (LR) statistic to test the estimated loss value and the actual loss value, which passes the test within a certain acceptance range, and under the original hypothesis, the statistic LR obeys a χ^2 distribution with degree of freedom of 1. The smaller the statistic LR, the larger the P value, indicating that in the model, the more accurate and the higher the credibility. When $P \geq 0.05$, its validity passed the post hoc test.

Table 9: $\mathrm{VaR_m}$ estimation results.

	p	Long position $\mathrm{VaR_m}$	Short position $\mathrm{VaR_m}$
Soybean oil	95%	−1.631120	1.556638
	99%	−2.643761	2.501126
Rapeseed oil	95%	−1.386436	1.394525
	99%	−2.696885	2.759419
Palm oil	95%	−1.641851	1.580744
	99%	−2.667628	2.471242

$$\mathrm{LR} = 2\ln\left[\left(1-\frac{N_u}{N}\right)^{N-N_u}\left(\frac{N_u}{N}\right)^{N_u}\right] - 2\ln\left[(1-p)^{N-N_u}p^{N_u}\right], \quad (12)$$

Table 10: VaRn backtesting results.

	Soybean oil		Rapeseed oil		Palm oil	
Long position VaRn						
p	99%	95%	99%	95%	99%	95%
N_u	33	138	32	146	27	148
LR	0.97685	0.00093	0.78150	0.69594	0.01651	0.69344
P	0.32297	0.97564	0.37668	0.40414	0.89773	0.40499
Short position VaRn						
p	99%	95%	99%	95%	99%	95%
N_u	37	160	29	158	27	142
LR	2.87393	3.40267	0.10733	3.43356	0.01651	0.10053
P	0.09002	0.06509	0.74320	0.06388	0.89773	75119

Table 11: $\mathrm{VaR_m}$ backtesting results.

	Soybean oil		Rapeseed oil		Palm oil	
Short position VaRm						
p	99%	95%	99%	95%	99%	95%
N_u	34	140	32	151	59	225
LR	1.36344	0.02063	0.78150	1.59221	27.0479	inf
P	0.24294	0.88577	0.37668	0.20701	$1.98E{-}07$	0
Short position VaRm						
p	99%	95%	99%	95%	99%	95%
N_u	37	160	29	165	80	239
LR	2.87393	3.40268	0.10733	5.93351	66.2146	inf
P	0.09002	0.06509	0.74320	0.01486	$4.04E{-}16$	0

where N_u is the number of days to failure and N is the total number of days observed. N_u/N is the frequency of failure and p is the confidence level.

The backtesting for the raw returns of the three futures indices are presented in Tables 10 and 11 for the long and short positions under the two threshold selection methods, respectively.

From Tables 10 and 11, it can be seen that the palm oil futures index is exposed to greater risk than the other two futures indices at the 99% and 95% confidence levels. The reason is that the gap between China's production and demand ranks among the top in the world, and China is excessively dependent on imports of palm oil. The EGAS-SKST-POT model under the threshold selected using the nonparametric method, the number of days to failure is closer to the theoretical number of days and the VaR values of long and short positions under the model pass the model backtesting, proving that the model is feasible. The use of this approach enables a significant increase in the accuracy of the model, and out-of-sample forecasting ability. In contrast, the thresholds based on the Hill estimator and the empirical mean-excess function deviate significantly and the VaR values for long and short positions under the model do not all pass the model backtesting.

4. Conclusion

The main objective of this paper is to apply EVT and the EGAS model to the Chinese vegetable oil futures index by targeting the characteristics of aggregation, persistence and asymmetry of daily returns in the Chinese stock market. First, the standard residual series based on the SKST distribution is inscribed through the EGAS(1,1) model, and a nonparametric quantile-based approach is adopted to select the threshold and apply the POT method in extreme value theory to calculate VaR values and perform backtesting. The study shows that the nonparametric method proposed in the article is able to select suitable thresholds and that suitable estimates can be obtained by fitting the GPD distribution for data where the new series exceeds the threshold, as well as the feasibility of the EGAS model on the China Futures Index.

Based on the empirical analysis of the value at risk of soybean oil, rapeseed oil, and palm oil futures indexes, the following suggestions are put forward:

First of all, in order to prevent the price fluctuation and risk of vegetable oil futures market, we should give full play to the price discovery and hedging functions of futures market. In the current situation of increasing price volatility in the futures market, it is necessary to strengthen effective monitoring of vegetable oil futures prices, improve the financial market supervision system, and prevent abnormal price volatility from negatively affecting other futures varieties. By monitoring and real-time analysis of abnormal events such as agricultural futures market information and other market information and policy changes, effective supervision of risk events can be achieved, and then timely warning can be given before the risk may break out, and timely response can be made after the risk occurs.

Second, strengthen the construction of futures market, vigorously develop futures market, increase trading varieties, control prices, give play to the unity and advance advantage of futures and options market information, and develop in the direction favorable to the development of financial market. Establish cross-sector agricultural product market risk early warning organization coordination mechanism. To solve the problems of incomplete and asymmetric information of agricultural products market, we should construct a multilevel matching and linkage information system of agricultural products market. Build agricultural market information sharing platform, form multidepartment organization and coordination mechanism.

Finally, as a result of the palm oil futures price volatility compared with other oil futures price volatility is larger, the sino-us trade friction and imposing import tariffs under the background of U.S. soybeans, necessary policy interventions can be taken to reduce oil futures price volatility, focus on palm oil futures varieties, broaden the import channel, implementing multiple imports of palm oil, add palm oil strategic reserve. Participants and investors in relevant industries should enhance policy attention and market sensitivity, comprehensively consider the factors of market fluctuations, and further strengthen rational production and investment awareness. In addition, the government should improve laws and regulations related to palm oil production and trade and reasonable market structure to ensure the safety and virtuous cycle of vegetable oil market and related markets.

Data Availability

The data used to support the results of this study are available from the Flush iFinD.

Conflicts of Interest

The authors declare that they have no conflicts of interest related to this work.

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Research Article

Dynamic Interdependence of Systematic Risks in Emerging Markets Economies: A Recursive-Based Frequency-Domain Approach

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We examine the interdependence of systematic risk in twenty emerging market economies. The interdependence structures are performed for subregional and regional categorizations of emerging markets, which have demonstrated financial openness over the years. Hence, the Kalman filter-based wavelet approach is adopted to execute the purpose of this study. The outcome from the contemporaneous correlations demonstrates that the degree of comovements among the equity betas varies. Moreover, from the wavelet multiple cross-correlations, Qatar, Brazil, Indonesia, and Czech Republic led for most timescales. Conversely, the equity betas of United Arab Emirates (Africa and Middle East), Argentina (Americas), China (Asia), and Russia (Europe) exhibit low degrees of integration with other systematic risk returns from each subregion. The low correlations, especially in the short term, of these countries within their respective regions signify less risk transmission and should be included in a portfolio of assets in determining investment risks. Generally, we find significant integration among systematic risks in emerging markets in the long term. We institute that the nature of interdependence in systematic risk has been heterogeneous across time. Accordingly, the equity betas increase with scale for most subregions and the emerging markets as a whole, implying that market interconnections heighten as the investment horizon is prolonged, revealing saturated markets with shocks. It is recommended that prudent liquidity policies are implemented to augment resilience to systematic risks susceptibilities in the long term. The findings present pertinent implications for portfolio diversification, policy decisions, investing risk, and risk management schemes.

1. Introduction

A debatable topic in the literature has been the definition and quantification of risk. Generally, risk is understood as the likelihood of an unfavorable consequence or the dispersion of expected returns and captured as standard deviation [1]. The theoretical rationale for using standard deviation as risk is based on Markowitz [2] who suggested the theory of mean-variance portfolio optimization.

Contrary to the Markowitz's portfolio theory, Sharpe [3] proposed a Capital Asset Pricing Model (CAPM). For a competitive market where all investors are mean-variance optimizers, the CAPM helps predict a direct linear relationship between a security's risk (systematic and unsystematic) and its return. On the other hand, Treynor [4, 5] advocates that the market is compensated for only systematic risk, calculated by beta–unsystematic risk, and can be disregarded by diversification, and thus, not compensated by the market.

Indeed, the cornerstone of modern finance theory is the risk-return trade-off. Most individuals are risk-averse–they require more returns but do not want to assume more risk. Therefore, only if they are rewarded with higher expected returns for bearing the risk can they invest in riskier securities. If the risk-return trade-off [2, 3, 6] is valid, asset portfolios with a high standard deviation should have high

expected returns. Contrarily, some studies advocate that there exists inverse relationship between risk and return (see, for example, [7–11]). In the same vein, studies that find a positive relationship between risk and return do not give adequate returns to compensate for a greater risk of high beta stocks [12, 13]. This phenomenon possibly provides an opportunity to reexamine risk minimization strategies/techniques in asset portfolios without necessarily dwelling much on the risk-return trade-off, which is not always guaranteed.

Globally, several studies have explored the performance of stock prices and assets returns [14–16]. In the case of emerging markets, studies have been conducted on CAPM and its international version ICAPM [1, 17, 18]. Nonetheless, the dynamics of systematic risk in the unique context of emerging markets are rarely explored. The rising role of emerging economies in international financial markets needs more focus in order to understand emerging markets, and their extent of comparability.

The growing economic size and technological consequence of emerging markets are among the principal forces determining the global economic and financial market setting. The ongoing capital market liberalization and recuperating market accessibility in emerging markets are triggering rethinking of the future of equity investing. Consequently, capital moves freely within emerging markets to facilitate trade and investment [19]. In this regard, understanding the dynamism of emerging markets, precisely, the speed and path of A shares inclusion, and the configuration and implementation in equity portfolios, especially Chinese market, is central to sound asset allocation decisions [20, 21]. Over the years, China and India have maximized their weight of gross domestic product (GDP) to about 32% and 15%, respectively, relative to other emerging economies fluctuating around 0.4% and 6% [21].

On the other hand, the size of a given stock market within emerging economies is not always linked to the corresponding country economic growth. This is evident since 1994 where market-capitalization weights of Brazil, Malaysia, and Mexico diminished as a percentage of the emerging markets index [21]. Correspondingly, less drastic change in economic weight of these countries was recorded. More distinctively, Korea and Taiwan received higher weights in the MSCI emerging index than the sizes of their economies, China's market-capitalization weight in the index heightened and converged with its share of GDP [21].

The undulating movements of economic and stock performance of emerging economies render their systematic risk worthy of investigating. As a result, investors would have to form reliable portfolios through appropriate assets allocations and portfolio rebalancing to minimize excessive volatility transmission among financial assets. The financial sector borders have expanded, so that individuals can invest in the markets of other countries in different parts of the world as a result of the financial markets integration theory [22]. Global investors' ability to acquire domestic assets, as well as local investors' ability to access international investment opportunities, is vital in enhancing financial markets integration (see, [23, 24]). Investors' risk preference, relative optimism, and information perception, to mention a few, are behavioral features that might impact the preparedness to invest overseas [25, 26]. As a result, the share of GDP from total capital flows within emerging markets has amplified over the years to respond to financial openness [21, 27]. In theory, financial openness fosters international risk-sharing and domestic consumption smoothing [28, 29].

Globalization in the financial system has changed the world economic architecture over few decades [30]. Despite the capital control management during the 2008 global financial crunch where investors were reluctant to invest overseas in risky investment vehicles, economies are recently liberalizing their financial sectors by reducing government regulations and restrictions on capital flows across borders. Capital accounts liberalization is germane to emerging markets, which have demonstrated similar magnitudes of economic and financial development, size and liquidity, and market accessibility to expand and engage aggressively with global markets. Nonetheless, knowledge of capital account liberalization in emerging markets offers many prospects along with challenges for the economic policymakers [30]. Thus, as it encourages assets allocation, it may resort to defect in monetary policy and financial crises. It becomes pertinent to examine the extent of financial openness of the individual emerging economies to facilitate comparisons through comovements and interdependence structures.

According to the Chinn and Ito database, as of 2019, financial openness of emerging countries considered in this study can be arranged as Czech Republic, Greece, Hungary, Qatar, United Arab Emirates, Chile, Saudi Arabia, Russia, Egypt, Malaysia, Thailand, Colombia, Indonesia, Argentina, Turkey, Brazil, China, South Africa, and India. Countries such as Czech Republic, Greece, Hungary, Qatar, and United Arab Emirates have attracted large amounts of capital inflows with success of earlier reforms meant to improve access to international capital markets. On the other hand, Turkey, Brazil, China, South Africa, and India are less opened to capital flows relative to their counterparts emerging economies. In this dynamic system, investors are concerned with the risk of their investments, and their humble desire is to create portfolios that are less volatile but more profitable.

A burgeoning number of empirical studies have exploited various models to measure the risk of financial assets and use them in portfolio selection. These include Dynamic Equicorrelation (DECO) model introduced by Engle and Kelly [31–33], CAPM beta model [1, 17, 34, 35], portfolio optimization for stock market using Value-at-Risk [16], Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in accordance with CAPM [36], cross-sectional regression using a weighted-least squares approach [37], and GARCH and GAS models through the model confidence set [38, 39].

None of these studies employed Kalman Filter (a recursive property) and multiple wavelet simultaneously to analyze interdependencies among systematic risk in emerging markets in a frequency domain. The traditional approach (CAPM) to beta estimation assumes stationarity; however, several factors influencing the comovements of

stocks with the market fluctuate over time [40]. Also, studies that compare Kalman Filter to GARCH models reveal that, due to the issues of forecast errors, Kalman Filter approach is tremendously preferred and considered as the most accurate forecast for equity betas (see, for instance, [41, 42]). Moreover, the wavelet multiple techniques provide the extent of lead/lag relationships and the degree of integration among more than two variables, which are frequency-dependent (see [22, 43, 44]).

The systematic risk of emerging Gulf Cooperation Council (GCC) equity markets was analyzed by Masih, Alzahrani and Al-Titi [45], and was consistent with the theoretical expectation that stock market investors have different time horizons due to different trading strategies, which showed a multiscale pattern in average beta coefficients in all GCC countries. This is because emerging markets in particular are less developed, involve more transaction costs, are highly dependent on individual investors, and are less liquid and prone to infrequent trading. While these findings are defining characteristics of stock markets of emerging economies in general, little is known about the integration of their systematic risks. It is worthy to note that a study that examines the degree of integration among systematic risks of emerging markets is timely.

In this study, we combine Kalman filter and wavelet techniques to analyze the frequency-dependent comovement of systematic risk of twenty emerging stock markets by country and region. This approach is necessary because market participants react to information at diverse timescales, resulting in very noisy market data. To correctly define this issue, the presence of different frequencies would accurately delineate the stock market participants' different investment intrinsic timescales, that is, short, medium, and long term. This is in line with the heterogeneous market hypothesis (HMH) as indicated by Müller et al. [46]. Also, the adaptive market hypothesis (AMH) engineered by Lo [47] suggests that markets evolve due to events and structural changes and adapt, and market efficiency varies in degree at different times. Therefore, frequency-domain analysis would minimize weak signals to maintain the true signals.

Particularly, the contributions of this study to prior studies are threefold. First, we estimate systematic risks returns of twenty emerging markets economies through the Kalman filter approach, which has a recursive property. Second, we investigate the degree of integration among these risks simultaneously to usher a full discussion of the nexus in a frequency domain. Third, to provide a detailed bloc investigation, analyses are performed for subregional and regional categories of emerging markets by the Morgan Stanley Capital International (MSCI). These are needed to enhance knowledge on capital account liberalization in emerging markets to deliver prospects along with challenges for the economic policymakers. Thus, as the patterns of integration among the systematic risk returns induce portfolio diversification and assets allocation strategies for investors, it may resort to defect in monetary policy and financial crises. By this, the paper contributes to literature as the first study to comprehensively examine the structure of systematic risk frequency-domain interdependence among emerging economies.

We found varying degree of contemporaneous correlation among the equity beta pairs for each country based on the regional analysis. It was also clear that lead/lag relationship was scale-dependent. As a result, the equity betas increase with scale for most subregions and the emerging markets as a whole, provided that market interconnections increase as the investment horizon is prolonged revealing saturated markets with shocks.

The rest of the paper is structured as follows. Sections 2 and 3 present the review of related literature and methodology. Results and discussions are presented in Section 4 and concluded in Section 5.

2. Literature Review

The investigation of systematic risk factor models is blatant in finance and economics literature. As noticed from asset pricing, only systematic risk or beta is priced, especially in the equilibrium state, thereby hindering anomalies conditions.

Prior literature on financial risks has welcomed rapid changes over time. The first strand of literature captures dispersion of expected returns through the standard deviation approach. The theoretical rationale for using standard deviation as risk is based on Markowitz's [2] theory of mean-variance portfolio optimization. The theory says that an investor will maximize its expected investment utility either by maximizing the expected return of a portfolio or by minimizing the variance of the portfolio if the returns of investors follow the normal distribution. While both assumptions are controversial, the mean-variance optimization theory of Markowitz has nevertheless provided a fruitful basis for the future growth of modern finance.

Contrary to the Markowitz's portfolio theory, the second strand of literature investigates risks from the standpoint of Sharpe's [3] Capital Asset Pricing Model (CAPM) [34, 35]. For a competitive market where all investors are mean-variance optimizers, the CAPM helps predict a direct linear relationship between a security's risk (systematic and unsystematic) and its return. On the other hand, Treynor [4, 5] advocates that the market is compensated for only systematic risk, is calculated by beta–unsystematic risk, and can be disregarded by diversification, and thus, not compensated by the market. For assets with positive beta, the rule of thumb is to purchase if the Treynor ratio is above the Securities Market Line (SML) and sell if it is below it. It is ideal for all assets to have a Treynor ratio less than or equal to that of the market. However, if, indeed, a positive relationship exists between risk and return, then an asset whose Treynor ratio is bigger than that of the market will probably yield more returns in accord with the systematic risk.

The third component of literature measures risk from the perspective of value at risk in line with the Basel III regulatory framework. This has induced a nascent and fledgling bodies of literature to account for risk in financial time series through a number of GARCH models [39, 48], as well as a combination of GARCH-based models with other models

[49–52]. These studies reveal the extent of volatility transmissions among financial assets either in a time varying or frequency-dependent perspective, or both with the quest of reducing noise from the data.

The fourth strand of literature measures risk based on volatility transmission among financial time series. This is done through either interconnectedness [23, 53], Boateng [54], or information flows among them [24, 55–57]. These studies reveal heterogeneity and adaptive behaviors of financial time series, thereby highlighting the importance of exploiting time and/frequency techniques.

In the context of emerging markets' equity returns, studies have advocated significant linkages [26, 58, 59]. However, little is known about their systematic risk returns linkages. But regarding insights from their equity returns linkages, similar dynamics are expected if the behavior of their equity returns are fully reflected in their systematic risk dynamics revealing some level of markets efficiency. Nonetheless, the heterogeneous nature and adaptive behaviors of financial markets due to the irrational behavior of investors would stimulate diverse outcomes at various investment horizons (short, medium, and long term).

In estimating systematic risk in the unique context of emerging markets, specifically in GCC economies, Masih et al.'s [45] outcome was consistent with the theoretical expectation that stock market investors have different time horizons due to different trading strategies, which showed a multiscale pattern in average beta coefficients in all GCC countries. This is because emerging markets in particular are less developed, involve more transaction costs, are highly dependent on individual investors, are less liquid and prone to infrequent trading. On the other hand, Owusu Junior et al. [60] assert that emerging markets employ prudent liquidity policies to enhance their resilience to systemic risks exposures. Moreover, a study by Arief [49] provides that diffusive and jump risk premia in Southeast Asia emerging markets have heterogeneous influence in other economies, and the outcome differs between high frequency and low frequency samples. However, studies on the integration among systematic risks of emerging markets revealing driving or lagging force are unknown, wherein capital moves freely within emerging markets to facilitate trade and investment [19], and the liberalization strategies instituted by most of their economies. A study on the interdependencies among systematic risks of emerging markets is needed to enhance knowledge on capital account liberalization towards delivering prospects along with challenges for the economic policymakers. It would also offer insights to investors on portfolio diversification and assets allocation strategies.

The novelty of this study is to utilize the Kalman filter technique, which is superior to GARCH in accurately forecasting equity betas [41, 42], in addition to the wavelet multiple techniques, which can describe the phenomenon in diverse investment horizons while reducing noise from the data to effectively assess the emerging markets' systematic risks integration. We utilize twenty emerging economies to capture a broad spectrum of the nexus in terms of subregional and regional integration. The following hypotheses are thus formulated with insights from prior theoretical and empirical outcomes in the context of emerging economies:

(a) There are strong interdependencies among systematic risks of emerging economies.

(b) The systematic risks interdependencies are scale-dependent.

3. Methodology

The analytical procedure is structured such that time-varying betas of the stock markets included in the study are obtained using the standard ICAPM based on the Kalman filter estimation. The Kalman filter is utilized in this study to estimate daily equity betas, due to its recursive property. This is followed by the wavelet multiple technique specifically, bivariate contemporary correlations (BCC), wavelet multiple correlations (WMC), and wavelet multiple cross-correlations (WMCC) as well defined by Gençay et al. [61] and Percival and Walden [62]. The wavelet multiple is specifically employed in this study to assess the dynamic interdependencies among the emerging markets.

3.1. The Kalman Filter Model. In the engineering literature of the 1960s, control engineers developed a significant concept called "state space" to describe structures that fluctuate over time [63]. Measurement and transition equations, which simultaneously direct a system's structure and dynamics, are represented in the general form of a state space model. An observation at time t in a linear combination of a number of variables in a state space model, referred to as state variables, makes up the state vector at time t. We designate the number of state variables by z and the $(z \times 1)$ vector by γ_t. The observation (measurement) equation can be presented as

$$Y_t = H_t \gamma_t + \eta_t, \tag{1}$$

where Y_t is the observation vector at time t; $\gamma_t = (z \times 1)$ process state vector at time t; $H_t = (z \times z)$ observation matrix; $\eta_t = (z \times 1)$ observation error, which is generally assumed to be Gaussian normal with zero mean, $\eta_t \sim N(0, \sigma_V^2)$.

The state variables may be specified as a minimum set of information conditioned on the past and present values, but the future state of time series is dependent only upon the present state. This is in line with the Markov property that the latest value of variables is appropriate to make forecasts other than past values. This is synonymous to the Random Walk Theory in the sense that stock prices follow a random movement when markets are efficient, and therefore, historical information is impossible to predict future stock prices.

Sharpe [3] and Lintner [64] advocate that Capital Asset Pricing Model (CAPM) defines the expected market rate of return of a specific asset in relation to the expected risk. The Sharpe-Lintner version of CAPM proposes a steady linear relationship between the expected excess return and undiversifiable risk (systematic risk) of holding financial asset. Beta has been one of the most common and accepted tools

used by financial economists and market experts in order to manage and assess risk. The standard CAPM postulates that

$$er_{i,t} = \alpha_t + \beta_{i,t}\left(r_{p,t}\right) + \varepsilon_i, \tag{2}$$

where $er_{i,t}$ denotes excess returns on individual stock i; $r_{p,t}$ signifies risk premium; $\beta_{i,t}$ shows beta of individual stock; ε_i is the disturbance term, which is normally and independently distributed with constant variance σ_ε^2. But–$er_{i,t} = re$–rf; and $r_{p,t} = rm - rf$; re = return on individual stock, rf = risk free rate; α_t and $\beta_{i,t}$ denote time-varying parameters; rm = return on the market.

To execute a time-varying structure of the ICAPM beta, we follow Faff, Hillier, and Hillier [65]; and Choudhry and Wu [41] by employing a state space model to incorporate unobserved variables with observable model and estimate them. The domestic CAPM can be extended to international settings and write a single factor international CAPM (ICAPM) as

$$ER_{i,t} = a_t + \beta_{i,t}\left(R_{p,t}\right) + \mu_{i,t}, \tag{3}$$

where $ER_{i,t}$ and $R_{p,t}$ are excess returns for i^{th} market portfolio and market risk premium, a_t means time-varying average return on market portfolio, and $\beta_{i,t}$ denotes time-varying beta returns of ith market portfolio $\mu_{i,t}$ = Disturbance term. But; $ER_{i,t} = Re$–Rf, and $r_{p,t} = Rm - Rf$; and; Re = return on the market portfolio, Rf = risk free rate and Rm = return on the world portfolio.

The time-varying beta structure is clearly modelled within the Kalman filter framework to follow any stochastic process. The series of conditional intercepts and the parameters for the ICAPM are generated based on an initial set of priors due to the recursive nature of the Kalman filter. Equation (3) signifies the observation equation of the state space model, inferred from equation (1). This paper uses the type of random walk that offers the best characterization of the time-varying beta compared to the AR(1) and random coefficient types of transition equation in order not to encounter the difficulty of return series convergence. The transition equation can thus be presented as

$$\beta_{i,t}^{\text{Kalman}} = \beta_{i,t-1}^{\text{Kalman}} + \omega_t, \omega_t \sim N(0, \varnothing) \tag{4}$$

The state space model can be obtained from equations (3) and (4). Moreover, to forecast the future value, we express the prior conditionals necessary for using the Kalman filter as

$$\beta_0^{\text{Kalman}} \sim N\left(\beta_0^{\text{Kalman}}, P_0\right), \tag{5}$$

With the aid of the prior condition, we estimate the entire series of conditional beta based on the Kalman filter recursive property. The choice of Kalman Filter over its competitors such as GARCH is motivated by its superiority in accuracy in forecasting equity betas (see, for instance, [41, 42]).

3.2. Wavelet Multiple. Let $X_t = x_{1t}, x_{2t}, \ldots, x_{nt}$ follow a multivariate stochastic process, and let $W_{jt} = w_{1jt}, w_{2jt}, \ldots, w_{njt}$ be a resultant scale λ_j. MODWT is used to estimate wavelet coefficients. Fernández-Macho [66] postulated that the WMC is known as $\Omega X(\lambda_j)$ which is a customary of multiscale coherence estimated from X_t that is shown in equation (6). The coefficient of determination (R^2) square roots from the regression fashioned by the direct grouping of $w_{ijt}, i = 1, 2, \ldots, n$ variables that make R^2 maximize are estimated in every wavelet scale λ_j. Prior research has shown that supplementary regressions are unnecessary since R^2 fits the conditions for the regression of a variable z_i by a set of predictors $\{z_k, k \neq i\}$ that can be represented as $R_i^2 = 1–\rho^{-ii}$, where ρ^{ii} is the ith diagonal portion of the inverse of the complete correlation matrix P. Therefore, WMC is shown in the following equation:

$$\Omega X(\lambda j) = \left(1 - \frac{1}{\max \operatorname{diag} P_j^{-1}}\right)^{1/2}, \tag{6}$$

where Pj is an $(n \times n)$ correlation matrix in W_{jt}.

Fitted values of z_i from a theory of regression are $\widehat{z}_t$; therefore, the WMc is shown in the following equation:

$$\Omega X(\lambda j) = \operatorname{Corr}\left(w_{ijt}, \widehat{w}_{ijt}\right) = \frac{\operatorname{Cov}\left(w_{ijt}, \widehat{w}_{ijt}\right)}{\left(\operatorname{Var}\left(w_{ijt}\right)\operatorname{Var}\left(\widehat{w}_{ijt}\right)\right)^{1/2}}, \tag{7}$$

where w_{ij} is used to capitalize on $\Omega X(\lambda_j)$ and $\widehat{w}_{ijt}$ represents the fitted values in the regression of w_{ij} on the outstanding wavelet coefficients at scale λ_j.

Therefore, WMCC is known by permitting a lag τ amid fitted values and observed at individual scale λ_j

$$\Omega X, \tau\left(\lambda_j\right) = \operatorname{Corr}\left(w_{ijt}, \widehat{w}_{ijt+\tau}\right) = \frac{\operatorname{Cov}\left(w_{ijt}, \ddot{\widehat{w}}_{ijt+\tau}\right)}{\operatorname{Var}\left(w_{ijt}\right)\operatorname{Var}\left(\widehat{w}_{ijt+\tau}\right)}, \tag{8}$$

where for $n = 2$, WMCC and WMC unite with the cross-correlation and standard wavelet correlation.

To calculate WMCC and WMC, let $X = \{X_1, X_2, \ldots, X_T\}$ be the recognition of the multivariate stochastic process X_t for $t = 1, 2, \ldots, T$. MODWT of order J is linked to individual univariate time series $\{X_{1i}, \ldots, X_{1T}\}$, for $i = 1, 2, \ldots, n$, the Jlength $- T$ vectors of coefficients of MODWT $\widetilde{W}_j = \left\{\widetilde{W}_{j1}, \widetilde{W}_{j1}, \ldots, W\widetilde{W}_{j,T-1}\right\}$, for $j = 0, 1, \ldots, J$ is obtained.

In equation (10), a nonlinear function of all $n(n-1)/2$ wavelet correlations of scale λ_j and a steady estimator of wavelet correlation from the MODWT are shown in

$$\begin{aligned}\widetilde{\Omega} X\left(\lambda_j\right) &= \left(1 - \frac{1}{\operatorname{maxdiag} \widetilde{P}_j^{-1}}\right)^{1/2} = \operatorname{Corr}\left(\widetilde{w}_{ijt}, \widehat{\widetilde{w}}_{ijt}\right) \\ &= \frac{\operatorname{Cov}\left(\widetilde{w}_{ijt}, \widehat{\widetilde{w}}_{ijt}\right)}{\left(\operatorname{Var}\left(\widetilde{w}_{ijt}\right)\operatorname{Var}\left(\widehat{\widetilde{w}}_{ijt}\right)\right)^{1/2}},\end{aligned} \tag{9}$$

where $\widetilde{w}_{ij}$: the regression of the equivalent set of regressors $\left\{\widetilde{w}_{kj}, k \neq i\right\}$ optimizing the R^2, $\widehat{\widetilde{w}}_{ij}$ denotes meeting the requirements fitted values, and $L_j = (L-1)(2^j - 1)$ shows the

number of wavelet coefficients impacted by the boundary constraints associated with a length wavelet filter L and scale λ_j but $\widetilde{T} = T - L_j + 1$ shows the number of wavelet coefficients that are not influenced by boundary conditions.

Similarly, a reliable equation for the WMCC can be estimated as

$$\widetilde{\Omega}X, \tau(\lambda_j) = \mathrm{Corr}\left(\widetilde{w}_{ijt}, \widehat{\widetilde{w}}_{ijt+\tau}\right) = \frac{\mathrm{Cov}\left(\widetilde{w}_{ijt}, \widehat{\widetilde{w}}_{ijt+\tau}\right)}{\left(\mathrm{Var}\left(\widetilde{w}_{ijt}\right)\mathrm{Var}\left(\widehat{\widetilde{w}}_{ijt+\tau}\right)\right)^{1/2}}. \quad (10)$$

Fernández-Macho [66] applies the transformation arctan h (r), where arctan h (.) is the inverse hyperbolic tangent function for simplicity's sake, to estimate the confidence interval (CI) of WMC [43]. The confidence interval was estimated from the same thought of the realization of X in the calculation of WMC and WMCC and hence for $\widetilde{\Omega}X(\lambda_j)$ in equation (9), the $\widetilde{z}_j \sim F\aleph(z_j, (T/2^j - 3)^{-1})$, where $z_j = \mathrm{arctan}h(\Omega X(\lambda_j)), \widetilde{z}_j = \mathrm{arctan}h(\widetilde{\Omega}X(\lambda_j))$, and $F\aleph$ symbolize the folded normal distribution. Thus, an estimate $(1-\alpha)$ CI is represented by

$$\mathrm{CI}(1-\alpha)\left(\Omega X\left(\lambda_j\right)\right) = \tanh\left[\widetilde{z}_j - \frac{C_2}{\left(\left(T/2^j\right) - 3\right)^{1/2}}; \widetilde{z}_j + \frac{C_1}{\left(\left(T/2^j\right) - 3\right)^{1/2}}\right], \quad (11)$$

where the $F\aleph$ critical values C_1, C_2 are: $\Omega(C_1) + \Omega(C_1 - 2z^0) = 1 - \alpha/2$ and $\Omega(C_2) + \Omega(C_1 - 2z^0) = 2 - \alpha/2$ with $\Omega(.)$ as the standard normal distribution function and $\tanh(z^0) = \Omega_X^0(\lambda)$ as the value of a WMC calculated under the null hypothesis of no connection.

3.3. Data Sources and Description. The data used for the study consists of twenty emerging markets' daily stock returns as classified by the Morgan Stanley Capital International (MSCI), Global stock index returns and risk free rate proxied by the US 91-day treasury bill rate. The data span from 23rd August 2010 to 3rd November 2020, making up a total of 833 observations after the data were merged in R statistical software to have common date for equitable comparison. The suggested period was chosen to cover the US-China trade tension, Brexit, and the COVID-19 pandemic. The countries were selected based on consistent and reliable data availability for the chosen periods, yet it contains most of the essential markets of the emerging economies. Daily data was selected over monthly/yearly series because daily data uses better-off information to compensate for the rapid fluctuations of financial information [67]. The data on stock market indices and the US Treasury bill were obtained from EquityRT database.

We consider the US Treasury bill because its bonds are generally believed to be of the highest credit quality, being backed by the full faith and credit of the U.S. government, and interest rates of most developing and emerging economies are procyclical to those of the US (see, [68, 69]). Also, due to openness of capital accounts in most emerging economies, portfolio equity inflows in more open nations are largely susceptible to fluctuations in the US treasury rates than domestic returns [70]. Moreover, as posited by Nguyen, Nguyen, and Schinckus [71], sensitivity of emerging countries to the US provides reasonable stable numéraire in investors' minds. We do not control for any other macroeconomic condition in the analysis because fluctuations in the macro variables would enable us to effectively examine the systematic risk nexus in the emerging economies. The daily equity betas were obtained with the help of the Kalman Filter, due to its recursive property. The continuous compounded returns of the indices with $P_{i,t}$ as the price index of market i at time t, $R_{i,t}$, are calculated as follows: $R_{i,t} = \mathrm{Ln}(P_t/P_{t-1})$.

Table 1: Emerging Market Economies classification by region.

Africa & Middle East	Americas	Asia	Europe
Egypt	Argentina	China	Czech Republic
South Africa	Brazil	India	Greece
Qatar	Colombia	Indonesia	Hungary
Saudi Arabia	Chile	Malaysia	Russia
Turkey		Taiwan	
United Arab Emirates (UAE)		Thailand	

According to the MSCI [21], emerging markets currently consist of 27 emerging-market economies. However, due to consistent data availability for the chosen period, which covers most important economic events, the analysis is conducted on 20 countries. The remaining 7 stock markets returns were specifically expunged from the analysis due to limited number of data for the selected period. The sample of 20 is representative for the analysis because it covers the majority of countries within the regional categorization by the MSCI. Notwithstanding, these 20 emerging economies are touted to be speedily expanding and engaging aggressively with global markets. With the increase in financial markets integration, these economies are considered to depict similar dimensions of economic and financial development, size and liquidity, and market accessibility with time regarding several regional classifications. Moreover, these emerging markets are seen to be risky investment, owing to excessive political risks and currency exchange volatilities with high tendency to aggravate systematic risks. Consequently, investors of these markets should highly expect volatile returns although the potential gains from these emerging markets are sizeable, and highly comparable to their potential losses. It becomes well intentioned to focus the analysis based on subregional and entire regional (emerging markets) classifications to quantify the extent of interdependencies among the 20 emerging economies. The world emerging markets are categorized into three regions, that is, Americas; Asia; and Europe, Middle East and Africa (EMEA). To have an in-depth analysis of both regional and global interdependencies, we further categorize the emerging markets as shown in Table 1.

3.4. Descriptive Statistics. Figure 1 shows the graphical representation for equity beta indices and returns series of twenty countries from emerging market economies based on regions. An informal stationary test was done by analyzing

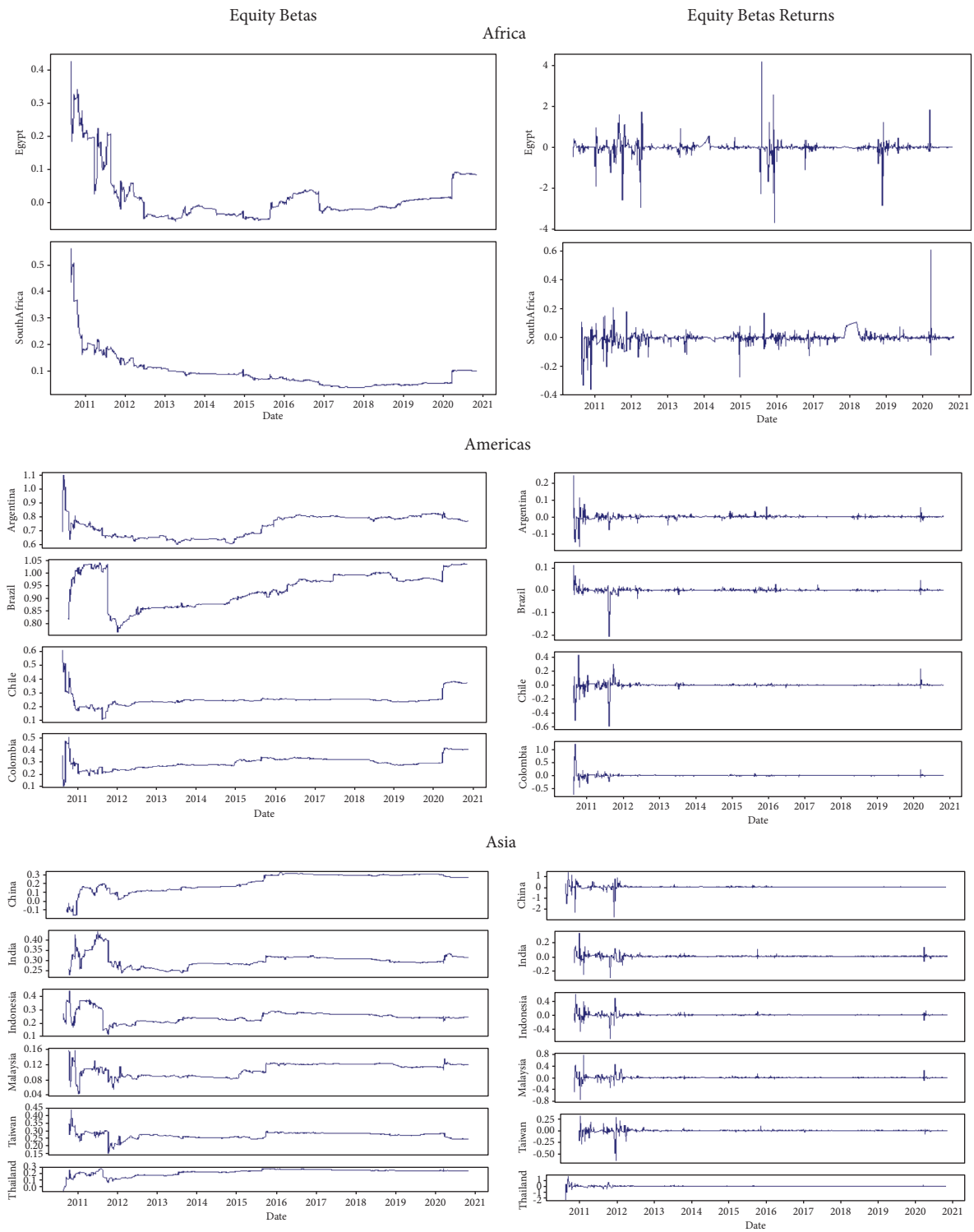

Figure 1: Continued.

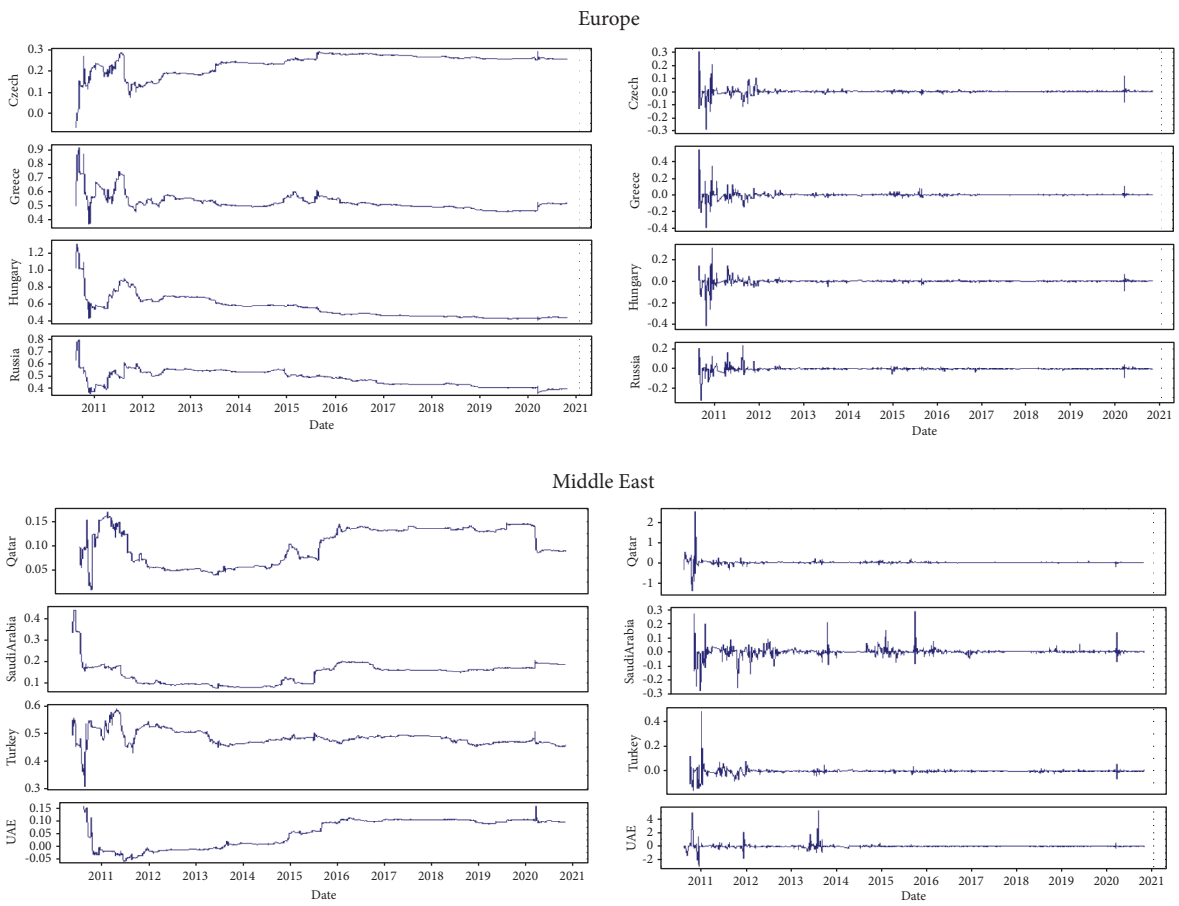

Figure 1: Graphical representation of equity betas of time series data.

the trend of the indices and returns used in the study. Most beta indices trend upwards for some time after the spike, which suggest that these series are nonstationary. This depicts that some countries within emerging market economies after the recent Global Financial Crisis have been experiencing increasing betas, except for Africa and Europe. Again, the returns tend to follow the same pattern. They become stationary after the first difference of all the variables as they revert around zero, as presented in Figure 1.

The following examines the equity beta indices extensively for each region within the emerging market economies to assess its fluctuations over the period of the study for careful comparison and policy decisions. A quick glance at the initial stage of the equity beta indices (plots) indicates a spike, specifically a large downward movement of betas for a short period of time. The outcome may not seem surprising since the period considered for the study takes into account the recovery from the 2008 Global Financial Crisis. Most equity beta indices trend upwards for some time after the downward spike. This depicts that some emerging market economies after the recent Global Financial Crisis have been experiencing increasing betas. At the latter part of the graph (approximately beyond 2016) for most countries, there seems to be an upward trending of betas. This may be due to shocks from the US-China trade tension, the 2020 Russia-Saudi Arabia oil price war, etc. and may require further analysis by researchers to ascertain the extent to which the presence of uncertainties is likely to influence systematic risk. Specifically, around 2020, there seem to be rising systematic risks for most emerging economies, and this could be due to adverse impacts from the COVID-19 pandemic shocks on global markets.

Moreover, considering countries whose beta trends are largely deviating from the rest within their respective regions including Brazil and Argentina from Americas and Turkey from the Middle East, the equity beta of China is showing a spike at the early stage of the trend, which suggests high inconsistency within the Asian region. Overall, the betas of Brazil seem to deviate graphically from the rest of the countries between 0.8 and 1.0 frequencies. This necessitates the stock market of Brazil to proceed with caution in order not to experience more volatile stock prices than the market in the near future. Notwithstanding, almost all the countries have a less than 1 beta, which is less than that of the market, demonstrating a defensive stock. Policy makers, governments, and international unions across the globe should fine-tune their economic policies to restore these betas to an appropriate level required by investors.

Table 2 depicts the descriptive statistics of the equity beta indices of the twenty Emerging Market Economies considered for this study. All betas had positive means with those of Egypt approaching zero. Moreover, the betas are less than 1, which signifies that the securities' prices are less volatile than the market. However, the beta of Brazil is noticed in approach 1, which requires immediate attention by existing and potential investors. As a result, investors of Brazilian stocks will demand higher equity premium to be compensated for taking on a higher risk of equity investing; nonetheless, the higher equity premium may not always be assured. This confirms the study of Araújo et al. [72] where the equity premium has been higher in Brazil, but the much higher Brazilian uncertainty to risk (volatility) discourages heavier investments in stocks. Again, most of the betas were positively skewed, for instance, African and European countries considered in this study. On the other hand, stock markets with the negatively skewed betas should proceed with caution since there is a potential for repeated greater losses due to the presence of increasing beta values. The equity beta of China is highly dispersed within the Asian region. This outcome may require further analysis to indicate the extent to which China can be considered as an open large country, and likely to receive shocks from trading with other countries. The same can also be said about Hungary in Europe. It could further be observed that all the dataset is not normally distributed, which supports the use of frequency-dependent techniques, consistent with the behavior of financial time series.

Table 2: Descriptive statistics of equity beta indices.

Regions/ countries	Mean	Std. dev.	Skewness	Kurtosis	Jarque-Bera
Africa					
Egypt	0.0146	0.0700	2.3699	9.8499	2408.3320***
South Africa	0.0858	0.0576	3.7026	23.8354	16970.6500***
Americas					
Argentina	0.7396	0.0730	−0.2937	2.3008	28.9454***
Brazil	0.9451	0.0620	−0.5407	2.4394	51.4980***
Chile	0.2562	0.0477	2.6434	15.4249	6328.3130***
Colombia	0.3070	0.0463	0.5792	4.7176	148.9597***
Asia					
China	0.2175	0.0962	−1.3803	5.1310	422.1302***
India	0.2981	0.0309	1.2916	7.0186	792.1197***
Indonesia	0.2486	0.0354	0.7719	5.8252	359.7646***
Malaysia	0.1091	0.0155	−0.7515	3.3042	81.6212***
Taiwan	0.2723	0.0192	−0.0079	12.2954	2998.9770***
Thailand	0.2394	0.0454	−2.2878	10.7940	2835.0460***
Europe					
Czech	0.4796	0.0908	1.4657	7.1039	882.7948***
Greece	0.5211	0.0515	2.5046	14.8178	5718.3300***
Hungary	0.5386	0.1185	1.8816	8.5420	1557.5630***
Russia	0.4770	0.0616	0.5276	3.4123	44.5436***
Middle East					
Qatar	0.1043	0.0363	−0.4772	1.7422	86.5308***
Saudi Arabia	0.1483	0.0457	1.0694	8.7787	1317.7890***
Turkey	0.4845	0.0265	0.0719	10.1953	1797.6560***
UAE	0.0636	0.0528	−0.6443	1.8087	106.8958***

4. Results

4.1. Comovement of Systematic Risk. The following section examines the regional and overall systematic risk comovement of emerging market economies. The regional analysis for the purpose of this study will be categorized as Africa and Middle East, Americas, Asia, and Europe. This categorization is shown to ascertain a substantial understanding of the dynamic interdependence of systematic risk in emerging markets, and to also draw inferences for economic policy decisions for each region. The overall analysis will enable the authors to clearly determine the countries that drive the comovement at various frequencies. The pictured plot incorporates the six scales into one plot to facilitate easy interpretation.

The study presents numerous wavelet cross correlations for various time scales with 15 days for the visualized plot of the wavelet (approximately half month). The classical plot helps us decide the multiple wavelet cross correlation graph's symmetry, while the visualized plot provides multiple cross correlations of the wavelet's strength. Again, the vertical long-dashed lines allow readers to accurately evaluate the time lag at which the strongest values of wavelet correlation are localized. Localizations at positive lag denote lagging variable and negative lag denote leading variable at the respective scales. The confidence interval spanning zero can also be easily recognized. At the zero lag of localization (dashed) lines, there is no lead or lag. Sections within the confidence interval spanning zero are shown in white. Localization implies the maximum values in the linear combination of all variables (equity betas) at the wavelet scales, which are indicated by dashed lines within the dotted lines (at all lags). A variable listed on a scale indicates the variable with the potential to lead or lag all the other variables. It implies that, at that scale, it has the maximum value in the linear combination of all the variables (equity betas) at the respective scales. When a dashed line accompanies a listed variable in the heatmap, then it becomes an actual lead (negative lag) or lag (positive lag) unless the dashed line is on the zero lag, which implies neither lead nor lag. Accordingly, the economic implication of the wavelet multiple cross-correlation (WMCC) is that it indicates the degree of interdependence between the variables and determines the most influential equity beta from a particular country at a specified wavelet scale to act as either a leading (first mover to respond to shocks) or lagging (the last variable to respond to shocks after the remaining variables) variable. To conclude, on the right side of each wavelet scale, the country that maximizes the multiple cross-correlations against a linear combination of the remaining variables is clearly presented. For the wavelet correlation, the wavelet coefficients are located within the 95 percent confidence interval.

The meaning of the scales in the care of data frequency of 5 days per week, lj, $j = 1, \ldots, s6$, of the wavelet factors is connected to times of, respectively, "2–4 days (intraweek scales), 4–8 days (weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (monthly to quarterly scale), and 64–128 days (quarterly to biannual

scale)" for scales 1–32, respectively [43, 44, 73]. These scales are represented in the y-axis from Figures 2–15.

4.1.1. Systematic Risk Comovement in the African and Middle East Regions. At 6 wavelet scales, the bivariate contemporary correlations are considered. The codes for the variables are Egypt (C1), South Africa (C2), Qatar (C3), Saudi Arabia (C4), Turkey (C5), and UAE (C6). For calculating wavelet correlation coefficients, the horizontal axis displays the combinations. If we switch from left to right, the dynamic interdependence between the systematic risks of Africa and Middle East becomes weaker. On the vertical axis, the wavelet scales reflect time periods.

In Figure 2, we present the wavelet correlation matrix for the systematic risk of Africa and Middle East across the six scales. We find a mix of direct and inverse relationships among the pairs. Qatar and Saudi Arabia demonstrated the maximum degrees of comovement with coefficients fluctuating over 0.29 to 0.95 at diverse time scales (scales 1–32) averaging 0.51, indicating the presence of extreme correlational values. Nonetheless, there are relatively lower levels of correlation between the systematic risk of United Arab Emirates and the rest of the countries. The result is similar to the study of Joseph and Fernandez [74], where UAE stock markets returns exhibited different behavior from other GCC stock markets returns. The study, moreover, confirms their suggestion for further research, where, in terms of risk, the stock markets of UAE would embellish and considered a defensive stock, which can be relied upon to form reliable portfolios.

Figure 3 represents the wavelet multiple correlation for the systematic risk nexus of Africa and Middle East. It could be argued that the nature of the correlation is far from identical both along time and across frequencies. From Figure 3, multiple correlations concentrate at large (above 0.7) at all-time scales except at scale 4, representing a monthly scale. It begins with a correlation coefficient of about 0.72 at intraweek scale, attaining minimum at weekly scale (0.42). The variation in the correlation continues until it reaches a peak of about 0.98 at quarterly to biannual scale. Overall, the systematic risk dynamics of Africa and Middle depict less connectedness in the medium term but converge in the long term at scale 32.

The wavelet multiple cross correlation coefficients are presented in Figure 4 and Table 3 depicting six wavelet scales. We find that the systematic risk of Qatar has the potential to lead or lag for most of the time scales and can maximize the multiple cross-correlations from a linear combination of the remaining systematic risks from monthly to biannual scale representing medium- and long-run comovement. The systematic risk of Turkey has the potential to lead or lag (at time 0) specifically at intraweek and weekly scales, Saudi Arabia has the potential to lead or lag at fortnight to monthly scales (at time 0), and Qatar leads (at times 0 and −1) at monthly to quarterly scale. The failure for the systematic risk of Egypt, South Africa, and United Arab Emirates to drive the relationship is due to less integration of their systematic risk returns within the Africa and Middle East regions. This can also be ascribed to the advancement of their stock markets, thereby minimizing their degree of dependence on the rest of the markets. Also, the systematic risk nexus within these countries stock markets was found to be low as compared to the rest. Empirically, in terms of stock returns driving tendency, the stock returns of Egypt and South Africa have the potential to lead most of the nexus among the developed stock market returns of crude oil producing countries in Africa. Likewise, Joseph and Fernandez [74] found out that United Arab Emirate's stock markets are considered to be developed and able to thrive even in times of economic downturn. Categorically, the stock markets of Egypt, South Africa, and United Arab Emirate are well developed and well integrated into emerging markets. In addition, the less interdependencies among the equity beta returns of some countries are beneficial to conservative investors since they offer diversification, hedge, and safe haven benefits.

4.1.2. Systematic Risk Comovement in the Americas Region. From Figure 5, we present the wavelet correlation matrix for systematic risk of Americas across the six scales. We find a mix of direct and inverse relationships among the pairs. Chile and Columbia demonstrated the maximum degrees of comovement with coefficients fluctuating over 0.03 to 0.74 at diverse time scales indicating the presence of extreme correlational values. The outcome of the study proves that the systematic risk of Argentina demonstrated relatively lower levels of correlation with the remaining systematic risk returns. This can be confirmed from the descriptive statistics of the study, where Argentina demonstrated extreme segmentation from the remaining countries within Americas. Moreover, there exists a high degree of negative comovements between the systematic risks of Brazil and Argentina but only in the long run. Contrarily, studies that evaluate the comovement between Argentina and Colombia stock markets find a significant relationship, but the comovements between Brazil, Chile, and Colombia are statistically significant [75]. This transcends to their systematic risks interdependence dynamics to establish that, generally, there exist high interdependencies between the systematic risks of Brazil, Chile, and Colombia, but less associated with Argentina. The low correlations between the systematic risk of Argentina and the remaining economies suggest that investors would minimize their investing risk when they include stocks of Argentina in a portfolio.

Figure 6 represents the wavelet multiple correlation for the systematic risk nexus of Americas. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. It begins with a correlation coefficient of about 0.41 at intraweek scale and attains maximum at fortnight scale (0.81). The variation in the correlation continues until it reaches about 0.79 at biannual to annual scale.

The wavelet multiple cross-correlation coefficients are presented in Table 4 depicting six wavelet scales. We find that systematic risk of Brazil has the potential to lead for most of the time scales and can maximize multiple cross-correlations

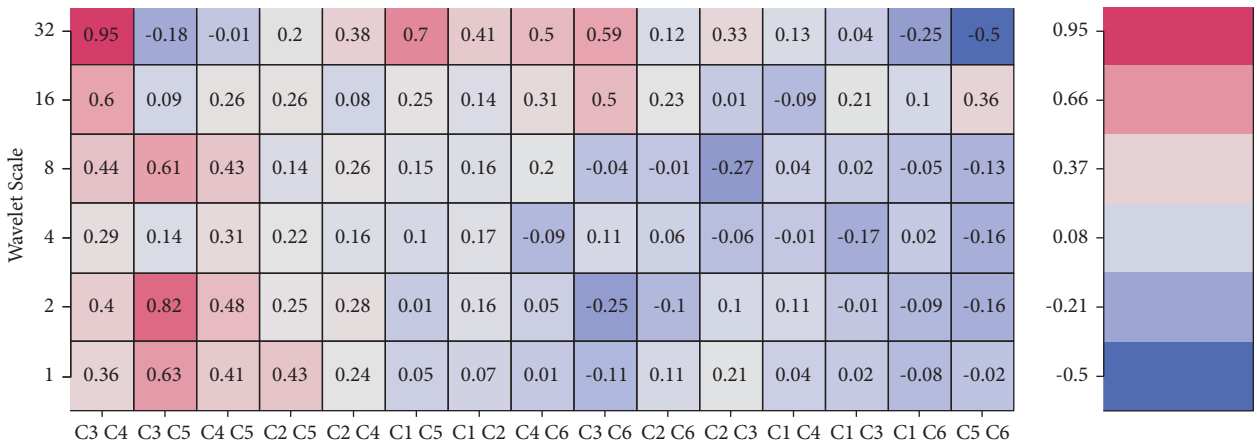

Figure 2: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are Egypt (C1), South Africa (C2), Qatar (C3), Saudi Arabia (C4), Turkey (C5), and UAE (C6).

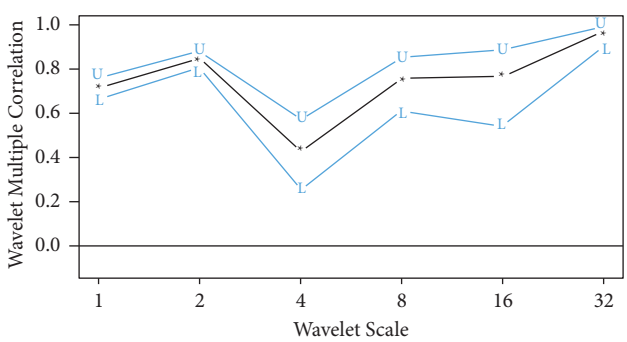

Figure 3: Wavelet multiple correlation between systematic risk of Africa and Middle East (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

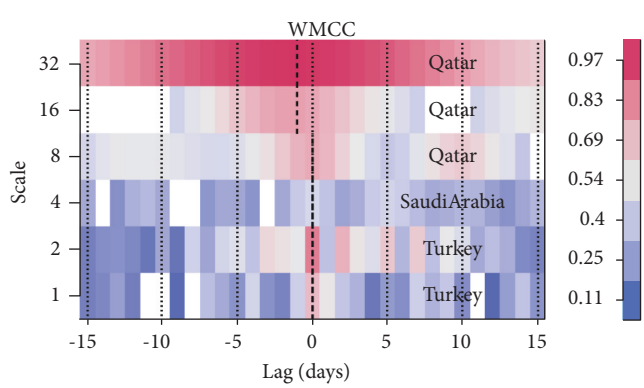

Figure 4: Wavelet multiple cross correlation between systematic risk of Africa and Middle East (18/08/2010–03/11/2020).

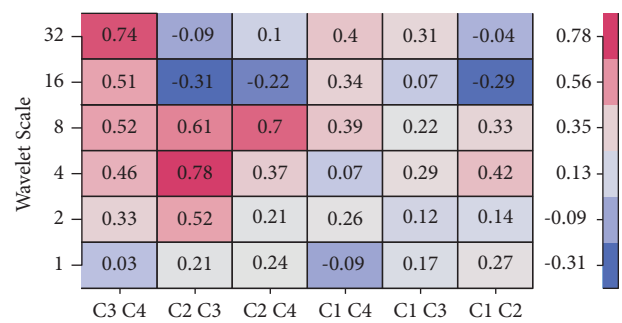

Figure 5: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are Argentina (C1), Brazil (C2), Chile (C3), and Columbia (C4).

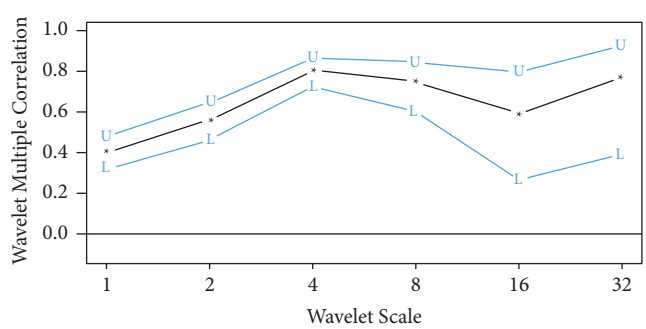

Figure 6: Wavelet multiple correlation between systematic risk of Americas (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

from a linear perspective of combination of the remaining systematic risks. The systematic risk of Brazil leads (at time −1 day) specifically at intraweek scale. Chile and Brazil have the potential to lead or lag (at time 0 day) at weekly and fortnightly scales, respectively. This is followed by Brazil again, which leads at monthly scale (at time −7 days). On the other hand, Colombia has the potential to lead or lag at monthly to quarterly scale (at time 0 day) but lags quarterly to biannual scale (at time 7 days). This implies that innovations as well as global uncertainties in Brazil, Chile, and Colombia have the potential to drive the systematic risk interdependence in Americas rendering Argentina to be less integrated.

4.1.3. Systematic Risk Comovement in the Asian Region. In Figure 8, we present the wavelet correlation matrix for systematic risk of Asia across the six scales. Surprisingly, we

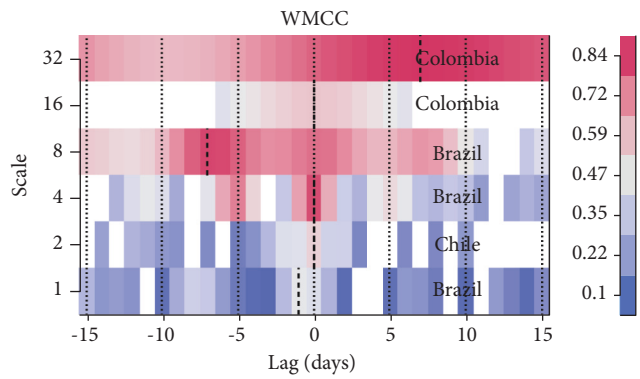

Figure 7: Wavelet multiple cross correlation between systematic risk of Americas (18/08/2010–03/11/2020).

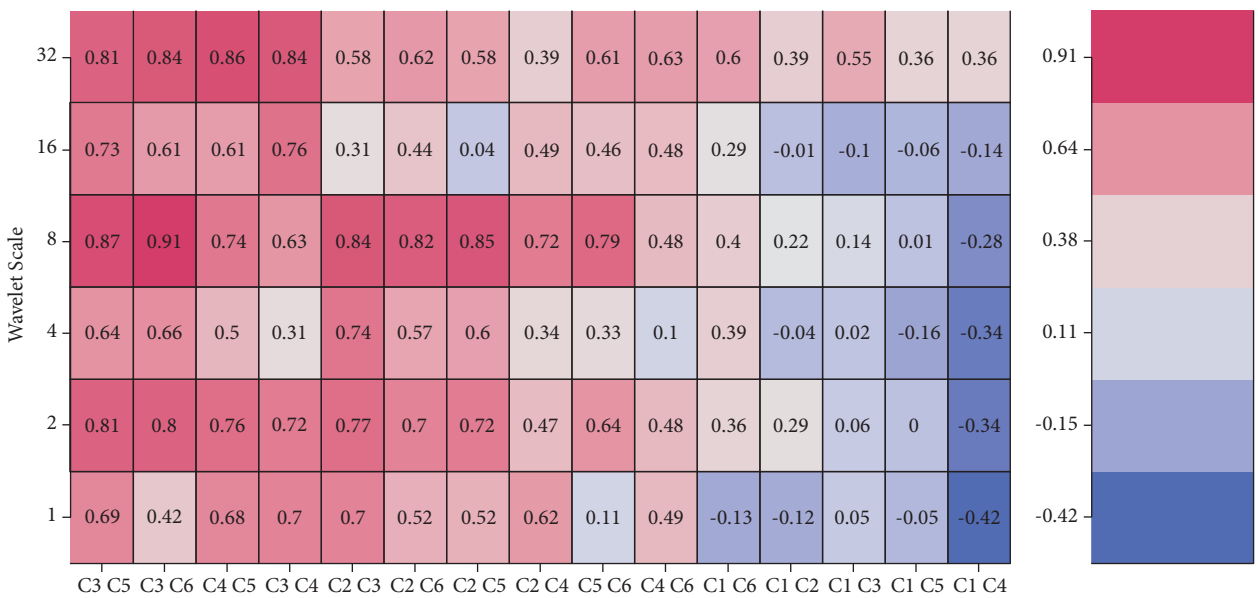

Figure 8: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are China (C1), India (C2), Indonesia (C3), Malaysia (C4), Thailand (C5), and Taiwan (C6).

find most positive relationships among the pairs, for instance, the comovements between Indonesia and Thailand; India and Indonesia; Indonesia and Malaysia; India and Taiwan, and among others. This suggests the uniformity in the systematic risk of Asia. However, there is a relatively lower levels of correlations between China and the remaining countries within the Asian region. This is so because China is among the top performing Asian countries in terms of nominal gross domestic product and features predominantly in the equities market, and thus, its systematic risk dynamics significantly segment from the remaining Asian countries. China is one of the very few countries in the emerging economies basket that has saw high earnings growth and high equity return against the backdrop of strong GDP growth [20]. However, the findings of Chen and Chiang [76] revealed that escalation of U.S. policy uncertainty has a significant adverse influence on Chinese stocks, thereby intensifying its systematic risk fluctuations as rightly confirmed from the descriptive statistics of the study. According to the volatility risk, "the EPU in Europe influences Asian countries the most and may be attributed to the extremely high trade dependence among these countries because the performance of international enterprises is mainly determined by the economic policies of their trading partners" [77]. Nonetheless, a portfolio with Chinese stock induces less shocks to other markets including global equities (see [20]), as shown by the negative comovements. This does not come as a surprise because the capital account of China is not fully liberalized. Despite the intention of the Chinese government to liberalize their capital account in recent years, the pace of liberalization remains ambiguous according to Liu, Spiegel and Zhang [78]. Consequently, portfolios inflows are more constrained in China. With a limited scope of investment assets, foreign financial institutions that invest in Chinese equities and bond markets do so through the Qualified Foreign Institutional Investor programs regarding a small quota [78, 79]. Restrictions on capital inflows within China are mostly

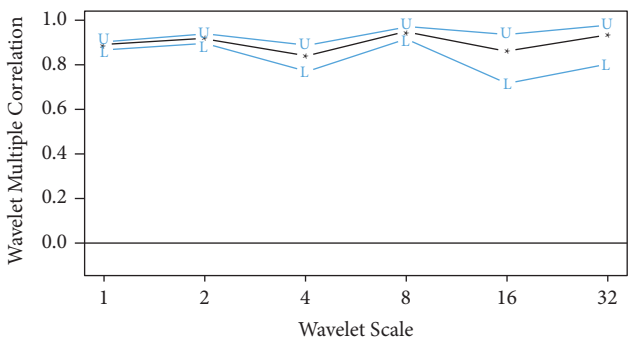

Figure 9: Wavelet multiple correlation between systematic risk of Asia (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

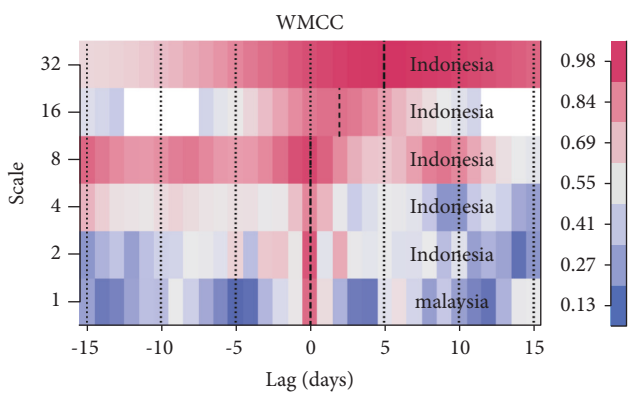

Figure 10: Wavelet multiple cross correlation between systematic risk of Asia (18/08/2010–03/11/2020).

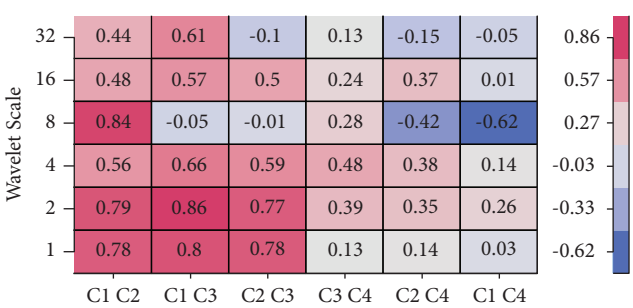

Figure 11: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are Czech Republic (C1), Greece (C2), Hungary (C3), and Russia (C4).

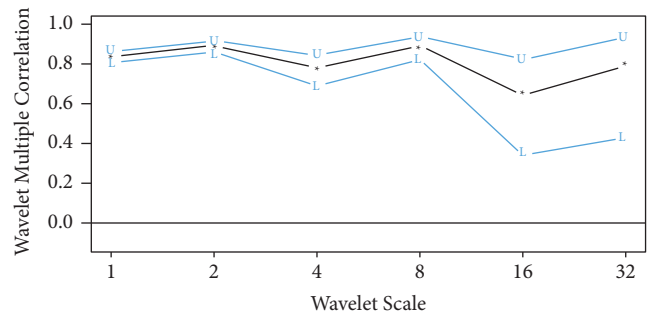

Figure 12: Wavelet multiple correlation between systematic risk of Europe (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

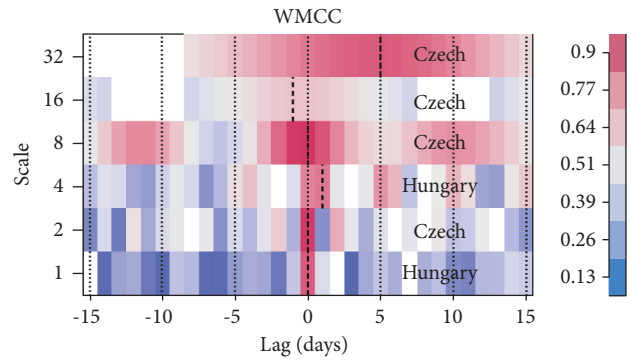

Figure 13: Wavelet multiple cross correlation between systematic risk of Europe 18/08/2010–03/11/2020).

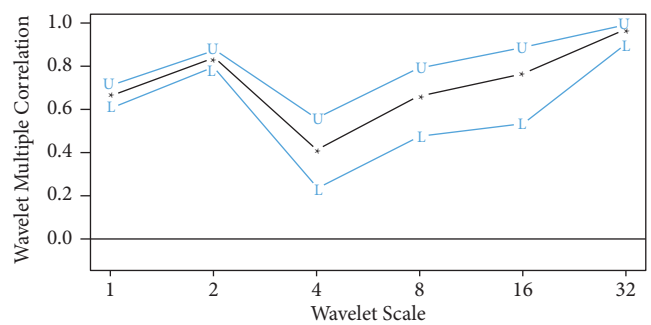

Figure 14: Wavelet multiple correlation between overall systematic risk of Emerging Markets (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

advanced to stabilize the currency, for instance, between 2000 and 2014. These are some of the practical reasons why China's systematic risk is less integrated.

Figure 9 represents the wavelet multiple correlation for the systematic nexus risk of Asia. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. In Figure 9, multiple correlations concentrate at large (above 0.82) at all-time scales. It begins with a correlation coefficient of about 0.88 at intraweek scale and attains minimum at fortnight (0.82) through to quarterly to biannual scale. The variation in the correlation continues until it reaches a peak of about 0.94 at biannual to annual scale. It can be analyzed that the systematic risk within Asia emerging markets is highly integrated. As a result, investors may less likely to reduce their portfolio risk when they form a portfolio within this region.

The wavelet multiple cross-correlation coefficients are presented in Table 5 depicting six wavelet scales. We find that systematic risk of Indonesia has the potential to lead and lag for most of the time scales (short-, medium-, and long-term dynamics). The systematic risk of Malaysia has the potential to lead or lag (at time 0) at intraweek scale. The systematic risk of Indonesia has the potential to lead and lag from weekly scale through to monthly scales but lags from

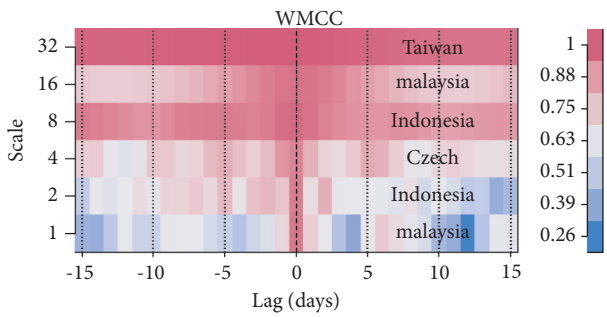

Figure 15: Wavelet multiple cross correlation between overall systematic risk of Emerging Markets (18/08/2010–03/11/2020).

Table 3: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lag (days)	Leading/lagging
1	0.717753473	0	Turkey
2	0.850666403	0	Turkey
3	0.429092917	0	Saudi Arabia
4	0.760799074	0	Qatar
5	0.784584139	−1	Qatar
6	0.973881045	−1	Qatar

Table 4: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lag (days)	Leading/lagging variable
1	0.461138768	−1	Brazil
2	0.56608047	0	Chile
3	0.809695585	0	Brazil
4	0.817564192	−7	Brazil
5	0.595102941	0	Colombia
6	0.839377245	7	Colombia

monthly to biannual scales, which depicts both short- to long-term dynamics. It could be seen that it is impossible for the systematic risk of China to lead or lag the systematic risk of the remaining Asian countries since the capital account of China is not fully liberalized [78]. Generally, the systematic risk of China, India, Thailand, and Taiwan is less connected with Indonesia and Malaysia. The outcome from Figure 10 indicates that the systematic risk of Indonesia lags in the long term, suggesting that it is the last nation within this region to respond to excess shocks.

4.1.4. Systematic Risk Comovement in the European Region. In Figure 11, we present the wavelet correlation matrix for systematic risk of Europe across the six scales. We find a mix of direct and inverse relationships among the pairs. The systematic risks of Czech Republic, Greece, and Hungary are highly correlated. However, Czech Republic and Greece exhibited the highest degree of comovement with coefficient fluctuating from 0.44 to 0.84. However, there are relatively lower levels of correlation between the systematic risk of Russia and the rest. Thus, the systematic risk of Russia demonstrated lower levels of correlation with the remaining countries in Europe. Accordingly, Russian stocks are most likely to experience diversification benefits. Generally, the

Table 5: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lags (days)	Leading/lagging variable
1	0.889421341	0	Malaysia
2	0.92081254	0	Indonesia
3	0.840432511	0	Indonesia
4	0.952318123	0	Indonesia
5	0.881861738	2	Indonesia
6	0.977211679	5	Indonesia

dynamic interdependence of the systematic risks is concentrated in the short term and medium term.

Figure 12 represents the wavelet multiple correlation for the systematic risk nexus of Europe. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. From Figure 12, multiple correlations fluctuate from 0.6 to 0.9, representing moderate to large comovements. It begins with a correlation coefficient of about 0.84 at intraweek scale and attains minimum (0.62) at monthly to quarterly scale. The variation in the correlation continues until it reaches scale 32 of about 0.78 at biannual scale.

The wavelet multiple cross correlation coefficients are presented in Table 6 depicting six wavelet scales. We find that systematic risk of Czech Republic has the potential to lead and/or lag at most time scales, and it can maximize the multiple cross-correlations from a linear perspective of combination of the remaining systematic risks representing the dynamics of short-, medium-, and long-run comovements. Similarly, Fedorova and Saleem [80] provided a strong evidence of direct linkages between the equity markets of Czech Republic and Hungary in terms of both returns and volatility. It can therefore be inferred from the outcome of Fedorova and Saleem [80] study that the dynamics of the stock returns and systematic risk returns of Czech Republic and Hungary are highly integrated in Europe. This suggests that the systematic risk of Czech Republic acts as a first mover and follower to external shocks from the medium to long term, whereas that of Hungary acts as a follower in the short-term.

4.1.5. Overall Systematic Risk Comovement of Emerging Market Economies. Figure 14 represents the wavelet multiple correlation for the systematic risk nexus of overall emerging markets. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. In Figure 14, multiple correlations concentrate at large (above 0.94) at all-time scales. It begins with a correlation coefficient of about 0.96 at intraweek scale and attains minimum at fortnight (0.94). The variation in the correlation continues until it reaches a peak of about 0.98 at biannual to annual scale. A critical glance of Figure 14 indicates that integration within emerging markets takes time before they converge in the long term. Consequently, systematic risk within emerging economies is amplified from long-term portfolio investment holdings. Investors who seek to minimize their portfolio risk within emerging markets are encouraged to capitalize on short- and medium-term equity

Table 6: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lags (days)	Leading/lagging variable
1	0.840230759	0	Hungary
2	0.892463734	0	Czech Republic
3	0.793805195	1	Hungary
4	0.896351128	0	Czech Republic
5	0.647701999	−1	Czech Republic
6	0.840041608	5	Czech Republic

Table 7: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lags (days)	Leader
1	0.958262149	0	Malaysia
2	0.948391306	0	Indonesia
3	0.958970521	0	Czech Republic
4	0.982771735	0	Indonesia
5	0.975318146	0	Malaysia
6	0.999798295	0	Taiwan

allocation and portfolio holdings. This exhibits the frequency-domain structure of the systematic risk integration in emerging market economies across the timescales.

The wavelet multiple cross correlation coefficients are presented in Table 7 depicting six wavelet scales. We find that systematic risk of Malaysia and Indonesia has the potential to lead for most of the time scales. The systematic risk of Malaysia has the potential to lead or lag (at time 0) specifically at intraweek scale and monthly to quarterly scale, Indonesia leads (at times) at weekly and monthly scales, Czech Republic has the potential to lead or lag at fortnight (at time 0), and Taiwan has the potential to lead or lag at quarterly to biannual scales (at time 0). This implies that the systematic risks of the twenty emerging market economies are driven by four countries, that is, Malaysia, Indonesia, Czech Republic, and Taiwan, at different investment horizons. That is, at each wavelet scale, an emerging country has a potential of driving or controlling the comovements, and there is a likelihood that uncertainty shocks are amplified within the leading countries in the systematic risk dynamics. To ensure risk minimization, global investors within these regions should hedge or use the correct asset allocation strategy.

4.2. Discussion. Evidence from the BCC demonstrated that the degree of correlation among the equity beta pairs for each country based on the regional analysis is scale-dependent. Generally, the equity betas of United Arab Emirates (Africa and Middle East), Argentina (Americas), China (Asia), and Russia (Europe) exhibit low degree of integration with other systematic risk returns from each region. The low correlations from these countries within their respective regions signify less risk transmission and should be included in a portfolio of assets in determining investment risks (see [20, 22, 26, 67]). Thus, domestic investors try to obtain diverse advantages from trading with other nations despite the contagion effect between financial markets that are highly interlinked after the onset of a shock [81, 82].

Likewise, from the WMC and WMCC analyses, the degree of integration among the equity betas increases with scale for most subregions and the emerging markets as a whole. This depicts that market connections increase as the investment horizon is prolonged revealing saturated markets with shocks. We indicate that the benefits of portfolio diversification seem greater at the short-run scale. As a result, systematic risk estimations in emerging markets require short time horizons [49] to benefit investors. This assertion agrees in terms of metal portfolio diversification as indicated by Tweneboah [73]. Also, in line with the study of Masih et al. [45], multiscale dynamics are predominant in the average beta of all GCC countries. The current study addresses the existence of multi-investment horizons due to multitrading strategies pursued by investors. With regard to other sectors, for instance, real estate global beta spillovers, the study of Liow and Newell [83] provides a substantial contribution to literature where global beta spillovers are significant and time-varying across the countries studied.

Specifically, it was revealed that it is impossible for the systematic risk of China to lead or lag the systematic risk of the remaining Asian countries. This is because the capital account of China is not fully liberalized [78] relative to other economies. In this regard, a portfolio with the Chinese stock transmits less shocks to other markets including global equities [20], irrespective of the fact that escalation of the U.S. policy uncertainty has a significant adverse influence on Chinese stocks to intensify its systematic risk fluctuations [76].

Furthermore, we analyzed the dynamics of each region with respect to which equity beta has the potential to serve as market leader in terms of systematic risk. From the scope of the study, Qatar (Africa & Middle East), Brazil (Americas), Indonesia (Asia), and Czech Republic (Europe) led at most of the time scales. The economic implication of this outcome is that the systematic risk in these countries is the first to respond and transmit shocks. Consequently, investors in these countries should carefully manage their investment portfolios. The dynamics to which the equity betas maximize the linear combination of the other equity betas for each region slightly changed when the overall analysis of the systematic risks was performed. Thus, the equity betas of Malaysia, Indonesia, Czech Republic, and Taiwan had the potential to lead or lag, but without a specific lead or lag. This reveals that emerging markets are highly interconnected [26, 58, 59].

Findings from the current study imply that a rise in systematic risk may produce a damaging influence on stock prices. This is because, theoretically, investors seek to be compensated with increased required rate of return during times of risk and uncertainties, which stimulates stock prices to fall, albeit the risk-return trade-off may not always be guaranteed. The increase in equity betas for most countries is consistent with the behavior of conservative investors who sell stock as risk hits the market. Conversely, "risk lover" investors at moments of increasing equity betas (systematic risk) will buy stocks at low prices and will be rewarded with risk premiums if stock prices reverse in the future [76, 84].

5. Conclusion

We employed the techniques of Kalman filter-based wavelet multiple approach. These tools enabled us to examine the degree of interdependence in the equity beta returns (systematic risk returns) of twenty emerging market economies and their implications for investing risk and risk management solutions such as asset allocation and portfolio diversification, but that cannot be attributed to specific risk of individual investments. With portfolio diversification, using the wavelet multiple analysis on the equity betas extracted with the help of Kalman filter, we minimized unsystematic risk to approach zero of different asset classes. Categorically, the paper makes a unique contribution to the interdependence literature by assessing regional and overall systematic risk (equity beta) lead/lag relationship in explaining the stock market shocks among the selected emerging markets. The preliminary analysis depicted high fluctuations of equity betas from 2010 to 2013, which can be attributed to the Eurozone crisis, and a positive shift in the equity beta index of most countries during the COVID-19 pandemic.

Outcomes from the BCC demonstrated that the degree of correlation among the equity beta pairs for most countries based on the regional analysis is scale-dependent. That is, the correlations fluctuate over time scales for each equity betas. In addition, there are less linkages between most emerging economies for the two-paired analysis, suggesting portfolio diversification between them. On the other hand, we found from the WMC and WMCC that the equity betas of Qatar, Brazil, Indonesia, and Czech Republic led at most of the time scales. The economic implication of this outcome is that the systematic risk in these countries is the first to respond and transmit shocks. However, we did not find a specific lead or lag when the overall analysis was performed. This accentuates the high integration of systematic risk returns of emerging markets economies. In general, by comparing the outcomes from the BCC to WMC and WMCC, it can be concluded that emerging markets are rather highly connected compositely than individually to significant markets such as Qatar, Brazil, Indonesia, Czech Republic, Malaysia, and Taiwan. We advocate that there are strong interdependencies among the systematic risks of emerging markets, and the benefit of portfolio diversification is scale-dependent, which is greater in the short run.

The interdependence structure among the systematic risks returns is heterogeneous and adaptive in line with the HMH [46] and AMH [47], which contradicts the principles of efficient market hypothesis by Fama [85]. Also, the spillover effects among similar or differing regional systematic risks are intensified by irrational investors' persisting search for contending risks to meet their portfolio goals to accentuate the competitive market hypothesis engineered by Owusu Junior, Frimpong et al. [23].

Moreover, the degree of integration among the equity betas increases with scale for most subregions and the emerging markets as a whole. This depicts that market connections increase as the investment horizon is prolonged, revealing saturated markets with shocks. In addition, the high comovements between systematic risks of most countries due to significant increase in cross-market linkages are in broad consensus with the Contagion studies. Consequently, markets with augmented linkages indicate that shocks in one market are easily transferable to other markets. Indeed, knowledge of capital account liberalization in emerging markets offers many prospects along with challenges for the economic policymakers. Policy makers, governments, and international unions across the globe should fine-tune their economic policies to restore these betas to an appropriate level required by investors.

In line with the MPT [2], investors who seek to minimize their portfolio risks can do so in the short term. In this manner, international investors can observe the markets and take advantage of the scale-dependent comovement dynamics. The outcome from this study dynamically reflects the systematic risk of emerging markets opportunity set, and to help investors meet global and regional asset allocation needs. However, as with equity allocation decisions, investors should be cautious and understand the risks of moving away from a market-capitalization-weighted portfolio.

It is recommended that emerging markets should improve their depth of investments by encouraging the involvement of investors, especially institutional investors. Integrating the emerging market economies and facilitating cross listing can minimize investing risk, improve liquidity, and mitigate thin trading. For instance, application of prudent liquidity policies is needed to enhance resilience to systematic risks susceptibilities in the long term. Moreover, the introduction of the market maker role and invigorating the trading mechanism in the emerging market economies can minimize the issues of transaction cost, plummet excessive volatility, and make prices faithfully represent their value. To end with, public offerings should be intensified to contribute to the expansion of trading in emerging markets by local and foreign savings, which may serve as diversification opportunities for global investors. It is established from extant literature that uncertainties have the potential of impacting stock markets, which may invariably heighten the systematic risk of a given country, and this poses a challenge for emerging markets to maximize their investment climate via efficient financial reforms in order to attract global investors.

The current study is limited to the use of frequency-dependent analysis, revealing only intrinsic times (investment horizons). Hence, absence of calendar time dimension in this study becomes a caveat of this study. Further studies may concentrate on network analysis towards revealing the centrality of the systematic risk dynamics, and the investigation of macroeconomic variables impact on systematic risk in emerging market economies. Also, analysis may be analyzed through a time-frequency technique to reveal the impacts of various markets events, which must have caused a structural break or regime switch worthy of research in this area. Moreover, the increasing awareness of transfer entropy, specifically, at less probability events as illustrated by most empirical literature [44, 57, 86] in finance, may contribute to the discussion on systematic risk interdependencies.

Data Availability

The data used in support of this study are available upon reasonable request to the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Do Volatilities Matter in the Interconnectedness between World Energy Commodities and Stock Markets of BRICS?

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Financial markets integration has resulted in high interconnectedness among the BRICS stock markets, which minimizes diversification potentials. This has increased investors' interest in the financialization of commodities to minimize their portfolio risks. However, the comovements between these assets do not operate in a vacuum, which requires that the role of volatilities be considered in tandem. The purpose of this study is to explore the interdependencies between energy commodities and stock markets of BRICS in the midst of relevant volatilities. For this reason, the wavelet techniques, biwavelet and partial wavelet, are employed. We find that positive comovements between energy commodities and stock markets of BRICS become stronger in the long-term. Furthermore, volatility has a long-term impact on the correlations between energy commodities and the BRICS stock market. We argue that the US Volatility Index, which measures investor anxiety and volatility in stock markets, has the biggest impact on the relationship between energy commodities and BRICS stock markets. Surprisingly, the correlations between energy commodities and Russian stock markets were strong enough to withstand the effects of volatilities. Hence, investors can use volatilities to hedge portfolio risks in energy commodities and stock markets in Brazil, India, China, and South Africa.

1. Introduction

The emergence of BRICS economies has become one of the significant developments in global politics. Governments from these economies have set high aims for this regional bloc since 2011 [1]. For instance, the Chinese government describes the BRICS as a significant force to extend South-South cooperation, whereas the Russian government argued that international relations with BRICS are a polycentric system [2]. It is important that the factors on which international relations are critically examined with respect to their role and importance to world economies over time. Most attribute the importance of BRICS to their increasing economic size. On the other hand, a common claim to their international relations can be attributed to their extensive natural resource wealth. Energy is abundant in the BRICS economies, which are heavily reliant on the production and export of these commodities [1].

The energy sectors of the BRICS economies supply over 40% of the world's energy, as they are both net energy imports (China and India) and net energy exporters (Russia, Brazil, and South Africa). Russia is a net exporter of energy resources, save uranium, according to the BRICS Energy Report [3], and consistently ranks first in worldwide gas exports. Russia ranks second in oil exports and third in coal exports. In 2017, China's crude oil imports surpassed those of the United States for the first time, making China the world's largest oil importer. China further surpassed Japan in 2018 to become the largest natural gas importer. After the USA and China, India is considered the third largest energy consumer in the world with about 6% of

global demand [3]. South Africa consumes the second most energy on the African continent. Because South Africa's oil and natural gas production is limited, the majority of these energy products are imported. South Africa, on the other hand, exports more than 45 million tons of coal to international markets each year.

Aside from the resource endowment of BRICS economies, most of their governments employ "resource diplomacy" in their foreign policy strategies. Resource wealth is argued to be one of the factors contributing to the unification of BRICS economies [4] and therefore is considered as "resource powers." However, there is arguably a significant distinction between the status of an energy resource power and a mere possession of energy resources. Dating from the resource curse, particularly in Africa, endowment with resources does not automatically translate into economic development, or even financial development. As argued by Stulberg [5], the ability for a state to utilize natural resources depends on its domestic institutional capacity to control economic activity within that sector. Consequently, the policy dimensions instituted by these economies are relevant in determining the translation of resource wealth into economic or financial benefits [1].

Although attempts to achieve sustainable development goals by many developing and emerging markets have been initiated based on policies and measures for energy conservation and emissions reduction, the increasing demands of energy within these regions require that dependence on fossil fuels cannot be disregarded over a short period [6]. As a result, fossil fuels have become irresistible and important commodity in the international trade market. The rapid rate of energy consumption unavoidably leads to an increase in resource trade [7]. Energy trade relations between economies are of great importance to ensure that energy supports economic activities [8], with high probability of supporting the development of stock markets [9–13].

The lower diversification potentials of the BRICS markets have induced empirical studies to inculcate other financial assets [11, 12, 14–16]. The broad consensus from these empirical studies has been the higher likelihoods of portfolio diversification, safe haven, or hedge benefits depending on the markets outcome.

A nascent and fledgling body of literature has considered the financialization in commodities [17–19] which has maximized interconnectedness and volatility spillover to minimize diversification potentials among commodities [20, 21] to rather provide diversification benefits for distinct asset classes such as stocks and bonds [19, 22]. The interesting dynamics of BRICS stock markets [14, 23] may provide a greater reference for portfolio diversification with commodities.

Despite the unflinching interest in BRICS stock markets, current literature still requires empirical evidence on their interconnectedness with world energy markets [11]. From the behavioural intentions of investors, diverse investors may choose to diversify risks in BRICS stock markets through the energy markets which have faced rapid ramifications over time. This has brought about recent empirical studies to examine the interdependence structure between energy markets and stock markets of BRICS [9–12, 24, 25]. Regardless of the interesting results obtained by these studies, Sadraoui et al. [11] posit that the global energy sector works under heightened uncertainties caused by significant variations in demand and prices. It is argued that fluctuations in international energy prices may be a path against which world uncertainties are diffused to all stock markets through contagion [11].

Similarly, BRICS markets are susceptible to fluctuations in macroeconomic and global market settings [22, 26]. It is worthy of note that the role of domestic factors in shaping the financial and economic dynamics of BRICS nations cannot be ignored; likewise, the influence of external factors on their economies is not overemphasised [22, 27]. This can be seen from series of global economic crises such as the 2008 global financial crisis and the COVID-19 pandemic which led to volatile capital flows and stock performance of BRICS. It is an undeniable fact beyond any reasonable doubt that strong and robust economic outcomes of world leading economies such as the US are advantageous for BRICS (even though the bloc was able to withstand capital flight due to tapering by the US federal reserve) whose (BRICS) economies share massive and economic trade links. To some extent, less robust economic outcomes in developed nations would plunge exports by BRICS to the developed economics, which eventually dwindles capital flows and investments to BRICS nations [11, 14, 22].

With the high integration between BRICS economies and the developed economies, shocks from the developed economies including the US can have ravaging effects on BRICS stock returns [26] whose energy is abundant and are heavily reliant on the production and export of these commodities [1]. Similar to the adverse relationship between the US VIX and that of the returns [28], there is high expectation that the former's relationship with stock market returns of BRICS would exhibit more ravaging outcomes. Likewise, the sensitivity of BRICS economies to the high integration within emerging economies and their significant role in energy production and consumption demand that the impact of volatilities within emerging markets and energy sector be investigated in detail. Moreover, to account for the impact of volatilities from the largest nonfinancial securities, the NASDAQ-100 volatility index is further employed. The NASDAQ-100 index is home to some of the innovative companies around the globe, and as such, a proxy for the world's preeminent large-capitalisation growth index. As a result, its volatility is regarded as the newest entrant in a trading space dominated by a single "fear gauge" known as the CBOE Volatility Index (VIX). Its VIX includes a large and variable number of money options (in, at, and out) that forms a quantity of annualised variance. Accordingly, global volatilities or uncertainties have a role to play within the interconnectedness between world energy markets and stock markets of BRICS. This is lacking in empirical literature in finance as most studies ignore the partial influence of volatilities on the comovements between world energy markets and stock markets of BRICS across frequency and time.

It becomes pertinent to quantify the extent to which uncertainties distort or meander the comovements between world energy markets and stock markets of BRICS. A recent

study by Junior et al. [14] examined the extent to which investor fear influences the interconnectedness between BRICS stock markets, and the impact was found to be significant. However, despite the exorbitant finance studies on the comovements between energy and stock markets, little is known about the impact of relevant volatilities or uncertainties within these markets in a time and frequency domain.

The contributions of this study to empirical literature are in two main folds. First, we examine the comovements between five important world energy markets and stock markets of BRICS in a time and frequency perspective using the biwavelet technique. The world energy commodities employed are global energy index (Aenergy), Brent crude oil, heating oil (Hoil), gasoline, and WTI crude oil. Second, we assess the impact of four relevant volatilities or uncertainties between the comovements of the world energy markets and BRICS stock markets through the partial wavelet. With the influence of volatilities on other financial assets regarding empirical literature, the Chicago Board Exchange Volatility Index of the US (VIX), Global Volatility Index (GV), Emerging Markets Volatility Index (EM), and Volatility in Energy Markets (VEnergy) were employed as relevant volatilities in the energy and BRICS markets. These volatilities are forward-looking other than historical to gauge uncertainties/fear within the interactions between the energy markets and BRICS stocks. Consequently, through the partial wavelet, the impact of a common interdependence can be investigated while assessing the comovements between the variables in a time and frequency dimension.

We found positive comovements between world energy commodities and stock markets of BRICS, especially in the long-term. In addition, volatilities have a significant long-term impact on the comovements between the energy commodities and the BRICS stock market. Specifically, we found that the US Volatility Index as a measure of investor fear and volatility in energy markets has the most impact on the nexus between stock commodities and the stock markets of the BRICS.

The rest of the article is organized as follows: the literature review is provided in Section 2; methodology is given in Section 3; Section 4 contains empirical results; and Section 5 concludes the study and contains guidance for further research.

2. Literature Review

The empirical discourse on the interdependencies among BRICS stock markets is blatant with a strong consensus of high integration [29–31]. However, the high integration within the BRIC markets has the potential of minimizing diversification benefits across time-frequencies. As averred by Kannadhasan and Das [32], strong comovements in BRICS economies entail a state near to perfect integration and may limit the benefits of arbitrage and portfolio diversification. But, due to the resistance of BRICS stocks to most uncertainty shocks, it becomes practically impossible for uncertainties to distort their high level of integration relative to being disintegrated regarding market bloc [14], revealing their synergistic properties to shocks. Accordingly, attention has been driven to forming portfolios with other assets, such as commodities to seek safe haven benefits [33]. Similarly, there are high similarities among commodities [34] which demands that an extension of assets classes for portfolio diversification be made.

The theoretical link between energy commodities and stock markets can emanate from the stock valuation model or monetary channel [35]. The stock valuation model assesses a stock by discounting all estimated future cash flows leading to either escalation in cost of production (for energy-consuming firms) that minimizes net present value or increases future profitability (for energy-producing firms) [13, 36–38]. That is, the impact of fluctuation in energy prices on stock prices largely depends on net-consumer or producer [39]. On the other hand, the monetary channel originates from higher discount rates due to surges in energy prices (regarding high inflationary pressures coupled with an upsurge in interest rates). A growing body of literature also accounts for this linkage based on speculative dynamics and contagion effects, concerning delayed responses to information, market over-reaction, mean reversion, investor sentiments, attention to extreme price changes, etc. [27, 35].

This is necessary for BRICS economies whose energy sector is huge and they are heavily reliant on the production and export of these commodities [1]. The energy sectors of the BRICS economies supply over 40% of the world's energy, as they are both net energy imports (China and India) and net energy exporters (Russia, Brazil, and South Africa). It becomes relevant that the nexus between energy markets and BRIC stock markets in light of uncertainties be adequately investigated, because the persistent plummeting of stock market performance or portfolios declines investors' trusts and confidence in the financial system [40].

As a result, the wavelet techniques have become a common instrument for investigating limited variations of power within time series to determine both prevailing modes of variability and how the modes change over time through decomposition due to the time and frequency dynamics of financial assets [13, 23, 41–43]. In comparison to other methods such as quantile regression [34, 38, 44, 45], GARCH models [46–48], entropy techniques [49–52], and wavelet multiple [14, 23, 43], do not account for both time and frequency dimensions simultaneously, wherein serious economic events in addition to investment horizons are necessary to clearly understanding financial and economic phenomenon.

Specifically, the biwavelet technique is adequate in revealing the lead/lag relationships between financial time series in both calendar and intrinsic times. Similar to the biwavelet, the partial wavelet divulges the impact of a common interdependence on the nexus or interconnectedness between two financial time series across time and frequency. The finance and economic relevance of the partial wavelet technique is the extent to which a third variable can transmit shocks to the level of interdependencies between two financial time series. This induces the extent of diversification, hedge, or safe haven power of a third variable

(which are volatility indices in the study's context) depending on market outcomes.

Thus, the biwavelet and partial wavelet techniques adequately respond to the heterogeneous market hypothesis (HMH) [53] (Müller et al., 1997) and adaptive market hypothesis (AMH) [54]. The time and frequency domain provided by the wavelets show stock market participants' various investing horizons, which is consistent with Müller et al.'s [53] HMH. Also, the adaptive market hypothesis (AMH) developed by Lo [54] proposes that markets evolve and market efficiency differs in degree at separate periods as a result of events and structural transformations.

Given the several projections [55–58] into the development of the BRIC market, coupled with the fact that news items are more contagious in the few decades than ever [59], resulting from financial market turbulence, there is the need to assess the degree of interconnectedness between energy commodities and stock markets of BRICS while integrating the partial impact of volatilities in line with the modern portfolio theory of Markowitz [60]. This would disclose the linkages between the markets across time and frequencies, making it easier to examine the operability of fundamental market dynamics. Investors, portfolio managers, and fund managers might make valid assessments of safe haven, hedges, and diversification chances based on the revealed relationships and market dynamics of world energy markets and BRIC markets. It would also give insights to governments on the extent of resource diplomacy in their foreign policy strategies towards enhancing financial development in light of uncertainties. As advocated by Junior et al. [14], investors can modify their risk choices by investigating volatilities, and it is hoped that world energy markets and regional bloc analyses can help relevant stakeholders such as investors, portfolio managers, risk managers, and others better appreciate the global and regional structure of volatility in financial assets.

3. Methodology

The biwavelet and partial wavelet techniques are specifically employed in this study.

3.1. Biwavelet. The biwavelet showed the nexus between energy commodities and stock markets of BRICS economies from time-frequency perspective. Their results are shown in a pictorial form using arrows that are pointing right and left as well as upward or downward. The first variable is designated by right arrows pointing upwards and left arrows pointing downwards and vice versa for left arrows pointing upwards and right arrows pointing downwards. A color palette and a surface color represent the nexus between the linked variables.

3.1.1. Continuous Wavelet Transform (CWT). Wavelet has two transformation techniques, namely, discrete wavelet transforms (DWTs) and continuous wavelet transform (CWTs). The paper focused on CWT because it does a better extraction advantage. CWT ensures decomposition in time series into elementary functions. Because every frequency is used in operation and the shifting of the wavelet function is a continuous process, CWT results are easier to interpret. (1) is presented depicting the mother wavelet as

$$\psi_{\acute{\imath},s}(t) = \sqrt{s}^{-1}\psi\left(t-\acute{\imath}\right)\left(s^{-1}\right),\ \psi(\bullet) \in L^2(R), \tag{1}$$

where $\sqrt{s}^{-1}$ is the normalization factor, pledging the mother wavelet to have a variance that is equal to one. Mathematically, it can be represented by $(\psi_{\acute{\imath},s}(t))^2 = 1$; $\acute{\imath}$ and s have been explained earlier. The Morlet wavelet equation is shown in the following equation:

$$\varphi^M(t) = \pi^{-1/4}e^{i\omega_o t}e^{-t^2/2}, \tag{2}$$

where ω_o represents the main frequency of the wavelet of a value set at 6 [61, 62].

A mother wavelet decomposition for a time series $x(t)$ can be represented in (3) following the study of Li et al. [63] as

$$w_x(\acute{\imath}, s) = \int_{-\infty}^{\infty} x(t)\sqrt{s}^{-1}\psi\left(\frac{t-\acute{\imath}}{s}\right)\mathrm{d}t, \tag{3}$$

where ψ is known to be complex conjugate in the mother wavelet function. Based on the chosen time-series factors and limiting it to the specific features of $\psi(\bullet)$, our end is $w_s(\acute{\imath}, s)$. As previously stated, the fundamental advantage of a CWT is the ability to dismantle and recreate the function $x(t) \in L^2(R)$

$$x(t) = \frac{1}{C_\varphi}\int_0^{\infty}\left[\int_0^{\infty} W_x(\acute{\imath}, s)\psi_{\acute{\imath},s}(t)d\acute{\imath}\right]\frac{ds}{s^2}, s > 0. \tag{4}$$

3.1.2. Wavelet Transform Coherence (WTC). Wavelet transformation coherence that is WTC is explained by Torrence and Compo [64] as a cross-absolute spectrum's squared value normalization to a single wavelet power spectrum. The equation of the squared wavelet coefficient is denoted in the following equation:

$$R^2(x, y) = \frac{\left|\rho\left(s^{-1}W_{xy}(\acute{\imath}, s)\right)\right|^2}{\rho\left(s^{-1}\left|W_x(\acute{\imath}, s)\right|^2\right)\rho\left(s^{-1}\left|W_y(\acute{\imath}, s)\right|^2\right)}, \tag{5}$$

where ρ is a smoothing factor used to stabilities resolution as well as significance, and squared wavelet coefficient ranges between 0 and 1; $0 \le R^2_{xy}(\acute{\imath}, s) \le 1$. A value close to 0 denotes a shaky link, whereas a number close to 1 denotes a strong link. WT illustrates a comprehensive nexus amid the time series variables in the time-frequency domain. To achieve stronger comovements, a brighter color is shown. The Monte Carlo procedure was issued to test the statistical significance of this nexus since cross wavelet transform coefficient theoretical distribution is difficult to tell [64].

3.1.3. WTC Phase Difference. The WTC phase difference shows in a specific time series the interruptions in the oscillation. Taking insight from Bloomfield et al. [65], the

difference in phase between $x(t)$ and $y(t)$ is shown in the following equation:

$$\varnothing_{xy}(\mathrm{i}, s) = \tan^{-1}\left(\frac{\mathfrak{J}\left\{S\left(s^{-1}W_{xy}(\mathrm{i}, s)\right)\right\}}{\mathfrak{R}\left\{S\left(s^{-1}W_{xy}(\mathrm{i}, s)\right)\right\}}\right), \tag{6}$$

where $\mathfrak{J}$ and $\mathfrak{R}$ used in (6) show imaginary operators and real operators individually.

3.2. Partial Wavelet Coherence (PWc). The PWc is used in literature to minimize the issue of "pure" correlation between time-series variables as well as control the effect of time series variable *z(t)* on the wavelet coherence between other two-time series variables $x(t)$ and $y(t)$ [14]. PWc is depicted in a similar equation to the partial correlation squared, as shown in the following equation:

$$R_p^2(x, y, z) = \frac{\left|R(x, y) - R(x, z) \bullet R(x, y)^*\right|^2}{[1 - R(x, z)]^2 [[1 - R(y, z)]]^2}, \tag{7}$$

where $R_p^2(x, y, z)$ is between 0 and 1. The paper, x, and y denote world energy commodity returns and BRICS stock returns while z denotes relevant volatilities. PWc uses Monte Carlo methods in estimation.

3.3. Data Sources and Description. The daily data in support of this study included five relevant energy commodities which are NASDAQ Commodity Energy as a measure of global energy index (Aenergy), Brent crude oil, heating oil (Hoil), gasoline, and WTI crude oil, in addition to four volatilities, Chicago Board Exchange Volatility Index of the US (VIX), DWS NASDAQ-100 Volatility (includes 100 of the largest nonfinancial securities listed on the NASDAQ Stock Market based on market capitalisation) which we proxy as Global Volatility Index for nonfinancial securities (GV), CBOE Emerging Markets ETF Volatility (EM), and CBOE Energy Sector ETF Volatility (VEnergy). Particularly, the GV is an improved measure of implied volatility of equity indices on the NASDAQ-10 Index, whereas the VEnergy measures the market's expectation of 30-day volatility implicit in the prices of near term energy-stocks options. Moreover, we employed daily stock prices of BRICS countries which are made up of Brazil (Ibovespa Index), Russia (Moscow Exchange Russia Index), India (NIFTY 500 Index), China (Shanghai Stock Exchange Composite Index), and South Africa (JSE/FTSE All Share Index). The daily data span was 26th April, 2012, to 31st March, 2021. The suggested period was selected where the beginning and end-points are primarily driven by consistent data availability. Notwithstanding, this period spans serious economic events such as the aftermath of the 2008 GFC, the Eurozone crisis, Brexit, crude oil price crashes, and the COVID-19 pandemic. The data on BRICS were gleaned from EquityRT, whereas energy commodities and volatility indices were obtained from investing.com. We utilized daily returns as $r_t = \ln P_t / P_{t-1}$, where r_t is the logarithmic returns, P_t is the current index), and P_{t-1} is the previous index.

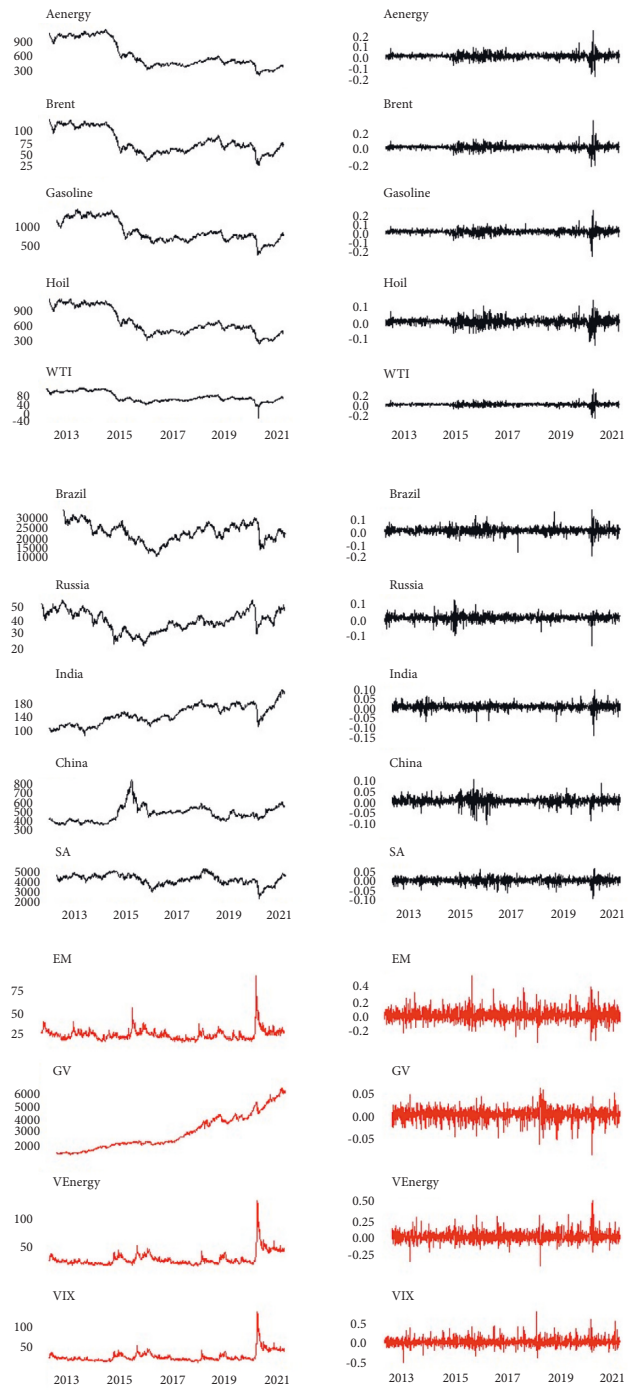

Figure 1: Plots of raw and returns series.

Figure 1 provides the time-varying prices and returns of energy commodities, volatilities, and stock markets of BRICS. We notice upwards and downwards movements in the variables. The sharp decline in most assets prices around 2015 may be attributable to the delayed effect of financial assets responds to the turbulence of the Eurozone crisis. Furthermore, the volatility indices show inverse relationships with the energy commodities and stock markets of BRICS, especially the GV. This may provide a useful signal for portfolio diversification. The rise in GV is not surprising because its VIX includes a large and variable number of

Table 1: Descriptive statistics.

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque–Bera
Aenergy	−0.00062	0.02259	−0.21889	17.06987	14869.73000***
Brent	−0.00035	0.02665	0.19331	24.17586	33661.16000***
Gasoline	−0.00023	0.02557	−1.22407	23.19561	31056.45000***
Hoil	−0.00052	0.02139	−0.28973	8.83366	2578.98600***
WTI	−0.00010	0.03114	0.20020	28.54743	48989.56000***
Brazil	−0.00026	0.02408	−0.64188	13.40565	8248.99800***
China	0.00018	0.01563	−0.67740	10.22979	4060.15200***
India	0.00041	0.01465	−1.06232	14.12231	9621.84100***
Russia	−0.00003	0.01785	−0.77477	12.15640	6471.64500***
SA	0.00001	0.01777	−0.73518	7.82979	1912.72500***
EM	−0.00007	0.07089	0.73956	7.71178	1830.16500***
GV	0.00082	0.01217	−0.75476	7.68888	1820.82700***
VEnergy	0.00028	0.06424	0.92790	10.00211	3937.70300***
VIX	0.00008	0.08816	1.16758	10.87065	5057.80800***

Note. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

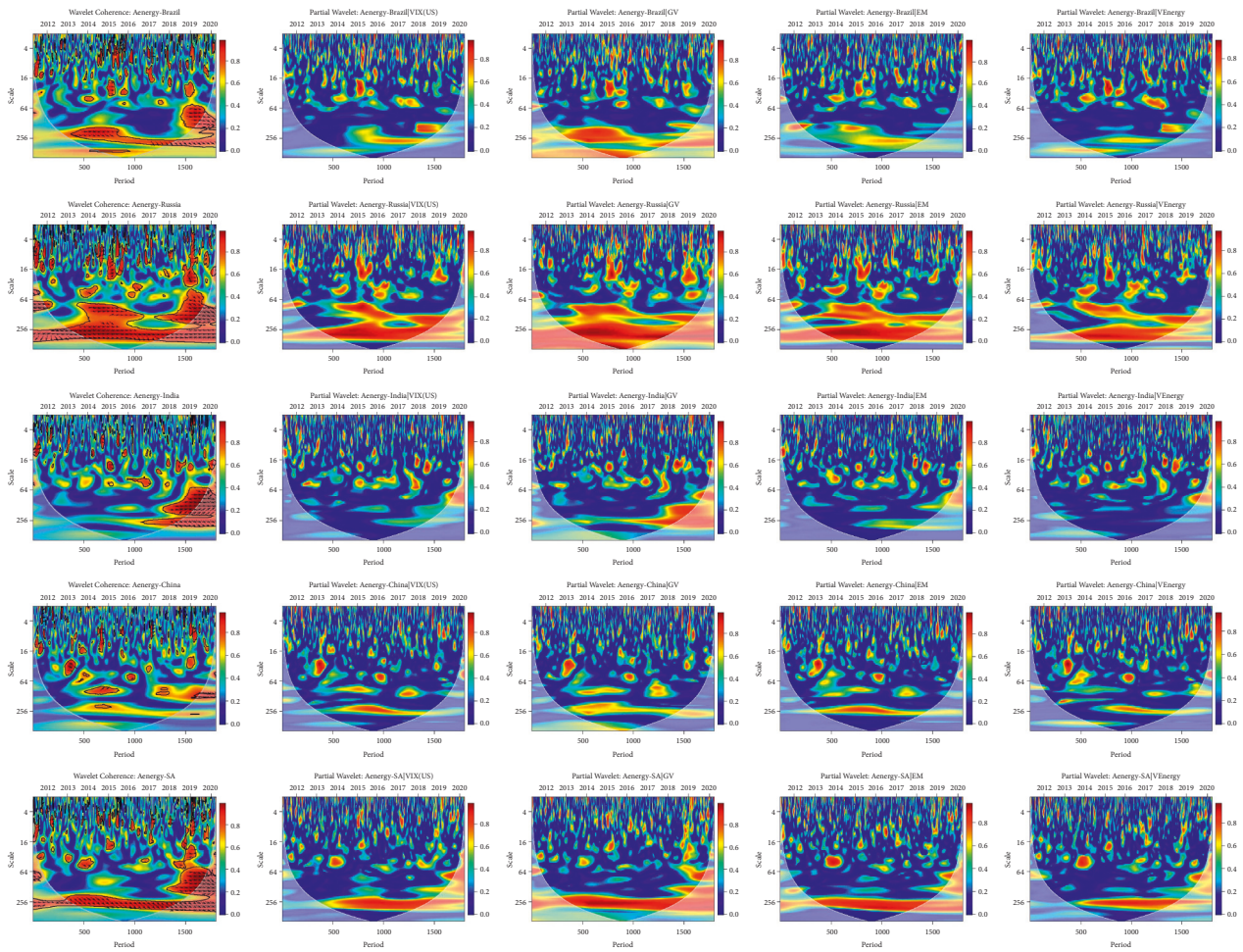

Figure 2: Comovements among global energy, BRICS, and volatility indices.

money options (in, at, and out) that forms a quantity of annualised variance, and thereby surging its value due to statistical noise from any of the three option types, and this impact is aggravating even during the COVID-19 pandemic. The sharp rise (fall) and fall (rise) of the other volatility indices (commodities and BRICS stocks) beyond 2019 suggest high likelihoods of markets rebound. The log-return plots demonstrate volatility clustering as expected due to the stylised facts of financial time series.

Table 1 shows the initial statistical analysis for the series of returns. The negative mean returns indicate the poor performance of financial assets over time whilst the positive

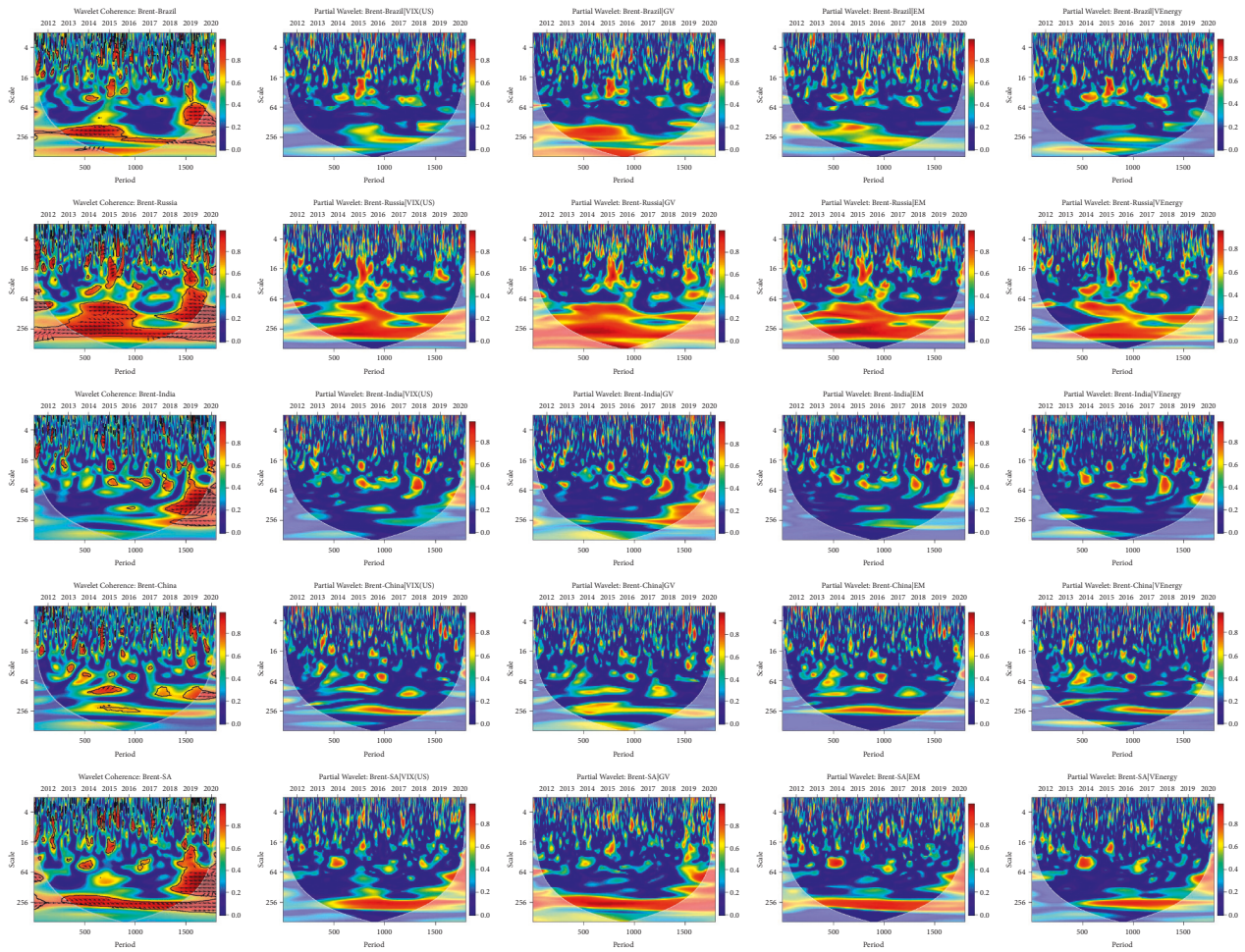

Figure 3: Comovements among Brent crude oil, BRICS, and volatility indices.

returns depict the tendency for markets to withstand shocks. The negative skewness specifically suggests that investments in these assets should be done with caution since there is a prospect for lower returns in a foreseeable period. Also, it can be observed from the Jarque–Bera statistic that all the series are not normally distributed.

4. Results and Discussion

The biwavelet and partial wavelets techniques are specifically presented in this section. We seek to assess the lead and lag relationships between energy commodities and BRICS stocks using the biwavelet technique. In addition, the partial impact of volatilities (as a common interdependence) on the comovements between energy commodities and BRICS stocks is investigated through the partial wavelet. Analyses are therefore mainly conducted on a time and frequency perspective.

4.1. Time-Frequency. The following section presents the time-frequency domain analysis of energy commodities and BRICS stock markets, as well as the partial impact of volatilities between the nexus. Right-pointing arrows and left-pointing arrows indicate whether the variables are moving in the same direction or in the opposite direction, respectively. The first variable is shown by right-pointing arrows upwards and left-pointing arrows downwards. Left-pointing arrows upwards and right-pointing arrows downwards, on the other hand, imply that the second variable leads. The surface color represents the degree of comovement between the matched series. The warm color denotes parts with a lot of interactions, whereas the cool color denotes regions with less interactions [14]. The region outside the cone of influence is insignificant. This is because they are beyond the 95% confidence level. Analyses are displayed for the short-, medium-, and long-terms at various calendar times in Figures 2–6.

From the biwavelet technique, we notice long-term significant positive comovements between the selected energy commodities and stock markets of BRICS. The positive comovements suggest high integration in the long-term dynamics which minimizes portfolio diversification. This is partly in line with the financialisation hypothesis as also found between gold and bitcoin in the study of Derbali et al. [66]. That is, both the energy and stock markets of BRICS move in the same direction with similar dynamics. The high integration between energy commodities and BRICS stock

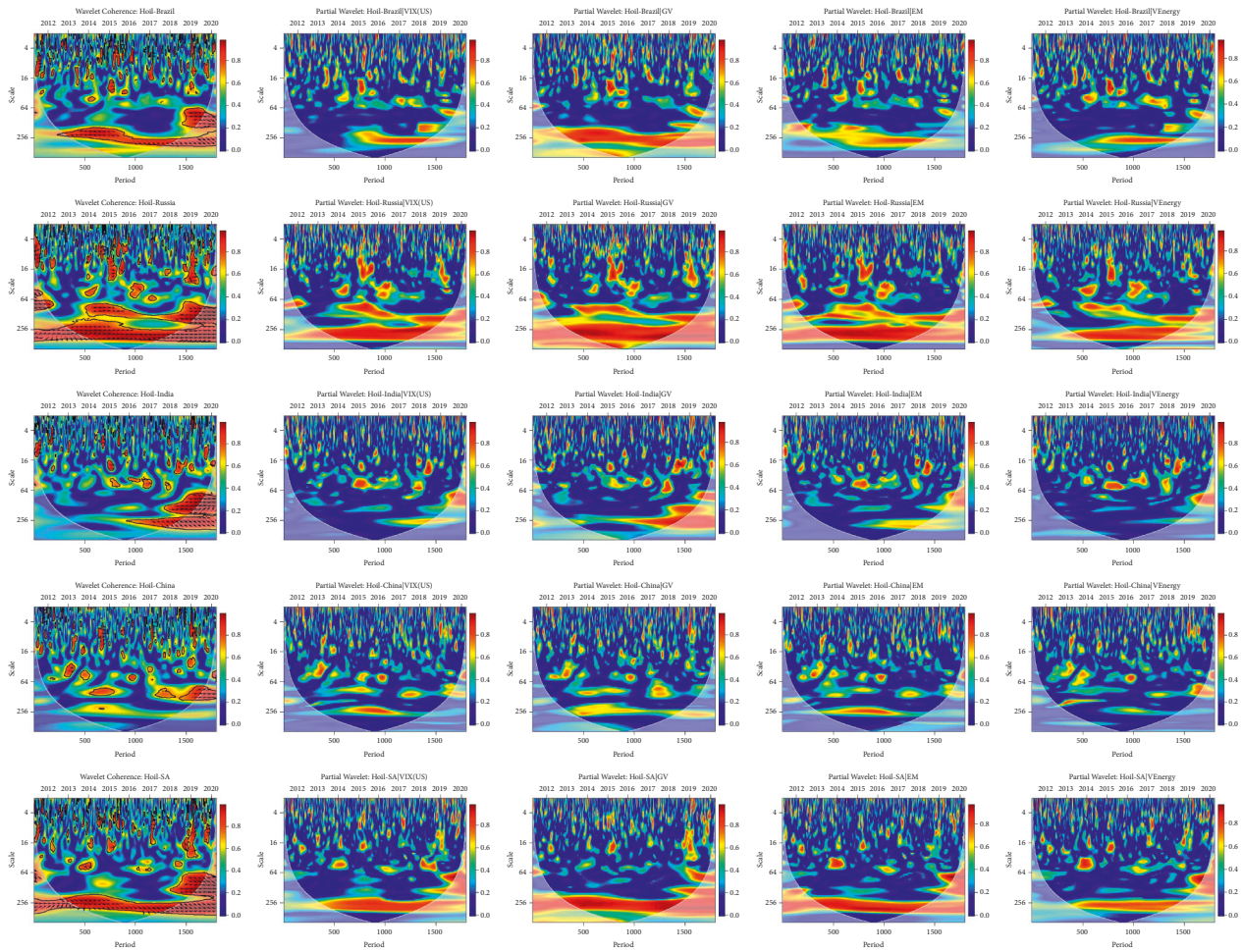

Figure 4: Comovements among heating oil, BRICS, and volatility indices.

markets highlights the assertion made by Abramova and Fituni [4] that resource wealth is one of the factors contributing to the unification of BRICS economies to enhance financial development, which makes those nations resource powers. Particularly, the Russian stock market demonstrates the most significant positive integration with all energy commodities relative to other constituents of BRICS. This is not daunting, because Russia is a net exporter of energy resources and has consistently ranked 1st in gas exports internationally. Furthermore, Russia is second to none in terms of oil exports and third in coal exports according to BRICS Energy Report [3].

In most cases, between 2012 and 2018, we find that the BRICS stock markets drive energy commodities in the long-term. This implies that, in the long-term, the BRICS stock markets act as a first mover or leader to predict the behaviour of energy commodities. It also suggests that the BRICS stock markets are the first variables to respond to shocks before the energy commodities. This highlights the degree of vulnerability of stock markets of BRICS to most uncertainties across time-frequency domain. Beyond 2018, there are traces of interdependencies between energy commodities and stock markets of BRICS in the medium- and long-terms where all markets have the potentials to either lead or lag. At this point, the markets have become saturated, and portfolio rebalancing becomes a relevant course of action to undertake. Yet, the level of integration between the markets is high which hinders portfolio diversification. Specifically, the strong long-term comovements between crude oil products (Brent and WTI) and the BRICS stock markets corroborate the outcome of Mensi et al. [25] and Mensi et al. [12]. Nonetheless, comovements of the energy commodities with India and China stocks (net energy imports) is less integrated as found in the study of Shahzad et al. [35] suggesting high diversification potentials.

The high positive comovements between energy commodities and BRICS stocks beyond 2018 span the COVID-19 pandemic period. At this point, investors assumed major losses which tumbled financial markets regarding strong uncertainty connected with the pandemic [33]. Moreover, it can be noticed from the biwavelet plots that high-rise in the spillover effects during the COVID-19 pandemic occurs mostly in the medium- and long-terms suggesting contagion effects during this investment horizon. In most cases, we find bidirectional relationship between energy commodities and BRICS stocks suggesting high degree of interconnectedness during the pandemic. Indeed, despite the rampant development of BRICS stock markets, resource wealth also

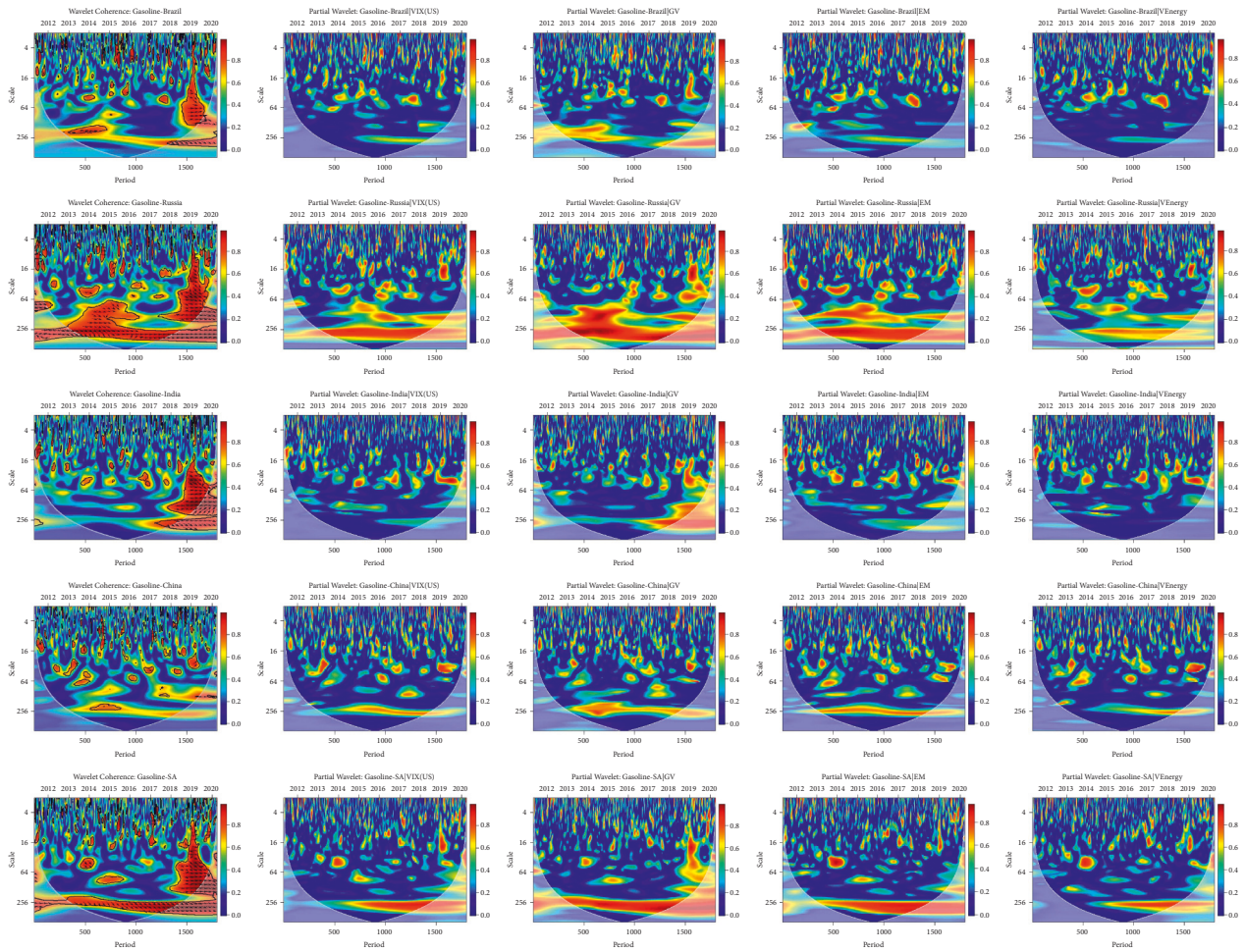

Figure 5: Comovements among gasoline, BRICS, and volatility indices.

strongly contributes to the unification of BRICS economies, to be touted as "resource powers" without overemphasis [4]. In this manner, our study supports the evidence that highlights the prevalent panic occasioned quick sell-outs and havoc in financial markets around the globe [33, 45, 49, 50, 67, 68]. It is the expectation of every investor and policymaker for the markets to recover and rebound quickly due to the ravaging impact of the pandemic.

However, since nations can enjoy the long-term sustainability of highly integrated economies, BRICS countries can shield themselves against uncertainties by hedging with relevant volatility indices. This can be inferred from the significant adverse impact of the volatility indices on the positive nexus between energy commodities and BRICS through the partial wavelet.

Throughout Figures 2–6, the US volatility index and volatility in energy markets have the most significant impact on the positive comovements between energy commodities and stock markets of BRICS. This indicates that in the midst of the volatility index of the United States and energy commodities, there is a distortion of the highly integrated energy commodities and BRICS stock markets both in time and frequency which increases the effectiveness of portfolio diversification. The adverse impact of the US VIX on the integration of BRICS stock markets can be observed from most empirical studies [14, 69, 70]. A second volatility of concern is the volatility in the energy markets. This is followed by emerging markets volatility which also has the tendency to distort the positive and significant comovements between energy commodities and stock markets of BRICS. In this sense, the implied volatility of equity indices on the NASDAQ-10 index (GV) has the least impact on the interconnectedness. However, the GV surges across time as found in the preliminary statistics; it has less relative direct link (as a common interdependence) on the comovements between energy commodities and BRICS stocks. It is required that future studies assess the impact of the GV on either energy commodities or BRICS stocks to adequately divulge its empirical properties. Notwithstanding, indeed, the impact of external shocks on the interconnectedness between energy commodities and BRICS stocks is eminent as indicated by Bouri et al. [22] and Bouri et al. [27].

The strong comovements in the long-term reiterate the heterogeneous [53] and adaptive behaviours of the markets [54] due to the changing dynamics of the markets across time and frequency. The comovements are also greater beyond 2019 in the medium- and long-terms when most economic activities were distorted due to the adverse impact

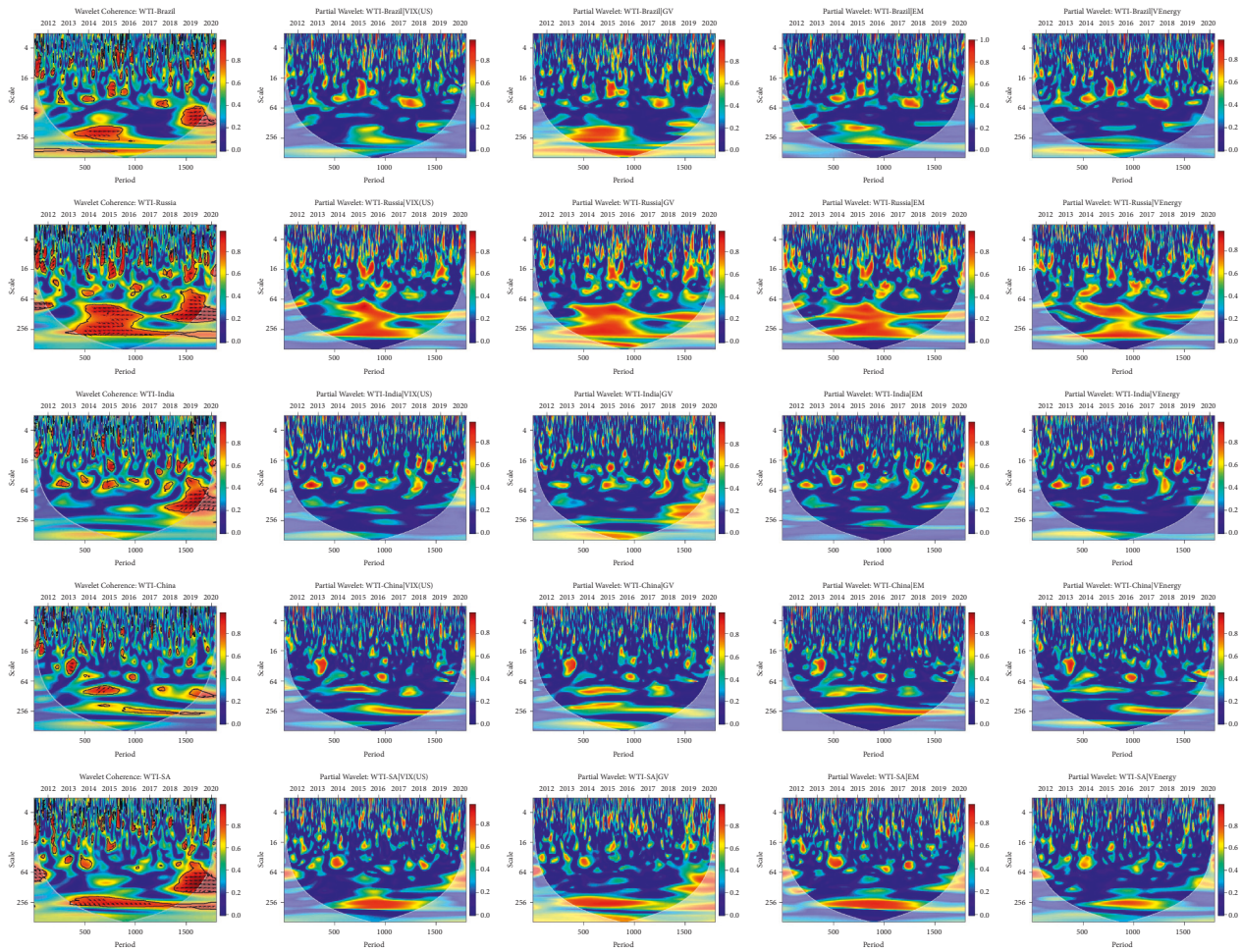

Figure 6: Comovements among WTI crude oil, BRICS, and volatility indices.

of the pandemic, requiring effective portfolio rebalancing. The high interdependencies between the markets suggest that financial markets begin to learn from each other coupled with similar spillover dynamics. That is, each market relies on each other which induces one market to react accordingly in times of shocks or contagion effect on the other market to influence investors' confidence. This hinders diversification potentials between markets, requiring portfolio rebalancing or redeployment of portfolios, especially in the long-term holdings of these assets. However, investors can gain by hedging against fluctuations in the high interdependencies between energy commodities and BRICS markets using relevant volatilities, such as the US VIX, as well as the US VIX and volatility in the energy markets can act as relevant safe haven instruments during the COVID-19 pandemic.

5. Conclusions

We employ wavelet techniques to examine the interconnectedness amid energy commodities returns and BRICS stocks returns, while considering the role that relevant volatilities play in tandem. Specifically, the biwavelet is employed to assess the comovements amid energy commodities returns and BRICS stocks returns. In addition, the partial wavelet is utilized to assess the impact of volatilities in the nexus between energy commodities returns and BRICS stock returns. We perform the analysis in a time-frequency perspective to reveal the heterogeneous and adaptive dynamics of the markets.

We found from the biwavelet technique that positive significant comovements exist among energy commodities and most of the stock markets of BRICS in the long-term and highlight the degree to which BRICS economies are touted as "energy resource powers." This implies that the energy markets and stock markets of BRICS are highly integrated, but mostly in the long-term. Specifically, the comovements between energy commodities and the Russian stock market were the strongest in the long-term, revealing the dominance of Russia in world energy commodities [3]. On the other hand, the integration of China's stock market is low, even in times of the COVID-19 pandemic, relative to its comovements with some selected international stock market indices in the pandemic [71]. Similar dynamics can be said of India. We assert that interconnectedness between energy commodities and stock markets of net energy importers (China and India) is low relative to that of net exporters (Russia, Brazil, and South Africa). This accentuates the fact that stock

markets of net exporters of energy commodities are more susceptible to fluctuations in the international energy market relative to net importers [35].

The result of the partial wavelet discloses that volatilities have a significant long-term impact on the comovements between the energy commodities and the stock market of BRICS. Specifically, we found that VIX (a measure of investor fear and volatility in stock markets) has the most impact on the nexus between energy commodities and the stock markets of the BRICS. Interestingly, the comovements between energy commodities and stock markets of Russia were strong enough to resist the adverse impact of volatilities. Hence, investors can hedge against portfolio risks within energy commodities and Brazil, India, China, and South Africa stocks using volatilities.

Findings from the study imply that diversification potentials vary between the world's energy markets and BRICS stock markets from the short-, medium-, and long-terms across calendar times, espousing the HMH [53] and AMH [54]. Moreover, the results offer indication on the predictableness of implied volatility indices on the connectedness between world energy markets and BRICS stock markets. We advocate that the US VIX is the dominant predictor of shocks in the energy-stock nexus. This is not surprising because the US stock market is huge with high tendency for its implied volatility to impact emerging stock markets [22]. We add that its impact on emerging stock markets has an analogous effect on world energy markets. This makes it effective to act as a common interdependence predictor of shocks rendering the notion that local investors worry more about other local and regional stock market uncertainties than the US market uncertainty, a potential inconclusive discourse. It is commendable that the US VIX has a transitioning effect on different classes of financial assets. Investors can therefore pay exceptional attention on the ravaging impact of the US VIX in meandering the nexus between energy and BRICS stock markets in times of portfolios formation and management. The results from this study do not only induce policymakers to secure stock markets against extreme world energy price movements in the future, but to effectively do so in light of several other volatilities, with the US VIX ablaze.

We recommend that investors, portfolio managers, and risk managers, among others should be wary of the heterogeneous and adaptive behaviour of the interconnectedness between word energy markets and BRIC stock markets at diverse market outcomes for appropriate rebalancing of portfolios. In addition, governments of BRICS should fine-tune their foreign policy strategies on the extent of resource diplomacy toward enhancing financial development with uncertainties in tandem.

The study covers energy commodities, whereas commodities markets exhibit heterogeneous dynamics. Similarly, the heightening interests in emerging markets render investigations of a broad spectrum of economies within this region prodigious. Other regional blocs and commodities from other sectors can be incorporated to examine their comovements in tandem with volatility indices. The impact of relevant uncertainty indices, including local volatilities on the nexus between country specific commodities can also be examined to respond to the high connectedness phenomenon among commodities. Subsequent studies can quantify the flow of information between the variables via multi-frequencies [50, 51, 72–75] (to add up to the spillover connectedness.

Data Availability

Data used in support of this study are available upon reasonable request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Dynamic Connectedness, Spillovers, and Delayed Contagion between Islamic and Conventional Bond Markets: Time- and Frequency-Domain Approach in COVID-19 Era

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Using the Baruník and Křehlík spillover index, the study examines the dynamic connectedness and spillovers between Islamic and conventional (G6) bond markets to reveal the time- and frequency-domain dynamics of the two asset classes under different market conditions. From August 22, 2012, through September 17, 2021, the daily bond yield indices for Islamic and G6 markets were employed. The findings reveal that volatility spillovers between and within Islamic and/or G6 bond markets are time- and frequency-dependent, although conventional bonds are more volatile than Islamic bonds during Black Swan periods. Across all time horizons, USA, UK, and Canada are the biggest producers of shocks to the Islamic and G6 markets, with Pakistan being the lowest shocks transmitter. During the European debt crisis, Brexit, and COVID-19 periods, the results underscore delayed contagious spillovers emanating from USA, Canada, and UK. With both the Islamic and G6 bond markets, short-term spillovers are more important than long-term spillovers. Investors should use their understanding of market trends and volatility to hedge their holdings against poorer asset returns when volatility spillover is more severe during market turmoil. Spillovers should be closely monitored by policymakers, since they jeopardise cross-market linkages.

1. Introduction

The recent coronavirus disease (COVID-19) pandemic, according to Giles et al. [1] and Baldwin and Di Mauro [2], is a global health catastrophe that has morphed into a severe economic crisis, culminating in unprecedented global economic and financial instability. Volatility spikes, repricing issues, liquidity difficulties, capital outflows, and currency devaluation have all been major financial market consequences of the COVID-19 epidemic [3, 4]. As a result, experts have predicted that COVID-19 would send the globe into a global recession. Shareholders become fearful and panicked as a consequence of the COVID-19 pandemic, and they detach their assets from the financial markets, causing share values to plummet. Similarly, owing to COVID-19, the debt market was disrupted, and bond buyers incurred losses that would be difficult to recoup [5]. Yarovaya et al. [6] noted that nearly all of the G7 countries lost between 30% and 42% of their stock market values, while global stocks, such as the S&P Dow Jones Indices and the S&P500 in the United States, lost approximately $6 trillion and $5 trillion, respectively, in market capitalisation [7]. Similarly, in line with the 2020 International Islamic Financial Market (IIFM) Report, Naeem, Billah, Marei, and Balli (2021) submitted that the growth rate in the Middle East and Central Asia areas dropped sharply from 1.2% to 2.8% between 2019 and 2020, which was worse than the GFC of 2008. It is not surprising that fresh Islamic bonds issuance is presently very slow as economies in major countries progressively open up [8].

These occurrences across global financial markets present shreds of evidence that suggests that the prices of assets in the uncertain times of the COVID-19 pandemic are reflective of the market conditions. This evidence partially supports the efficient market hypothesis (EMH), which

assumes that most asset prices are fairly priced based on the information available [9, 10]. In an efficient market, current asset prices materialise all available relevant information about a financial asset, such that the ideal projected return equates to the equilibrium return on the market. Future economic activity information inferred from current financial asset prices is a major conditioning factor that affects current financial asset prices. As a result, the broad uncertainties triggered by COVID-19 may drive global financial markets and rational investors to react and this follows two main hypotheses: the adaptive markets hypothesis (AMH) engineered by [11] and the heterogeneous markets hypothesis (HMH) developed by Müller et al. [12].

Thus, consequential to the COVID-19 pandemic and its associated information flows in existing markets, new markets may be created where economic agents (investors) are led to switch to or include several asset classes in their portfolios for hedging and diversifying risks. The switch from or inclusion of new assets to investment portfolios in Black Swan (Introduced by Taleb (2007) and describes events that occur randomly but are a part of human lives. Such events are characterised by (1) an outlier, deviating from usual expectations; (2) being accompanied by extreme impacts; and (3) being reasonable and foreseeable because reasons for its occurrence are imaginary after the fact. Black Swan events are shocks that occur on a large scale and have severe consequences on economic activity, social cohesion, and political stability.) periods requires that investors undergo some searches for safe havens (Baur and Lucey [13] define safe haven as any asset that has no correlation or is inversely correlated with another asset or portfolio during unusual (Black Swan) market conditions.) [13]. In brief, investors would be competing for lucrative returns on substitute assets to satisfy their investment needs. Corollary, the intensity of information flows and spillover across markets of the same and other asset classes is increased by rational investors. Also, irrational investors' have a never-ending quest for competing rewards and risks to meet portfolio objectives, which corroborates the competitive market hypothesis (CMH) propounded by Owusu Junior et al. [14]. The question now is, which asset class(es) is(are) predominantly available to investors during market crises and in which market type (Islamic or conventional)?

Gold, bonds, crude oil, bitcoins, and so forth are traditionally preferred by portfolio managers because they are predominantly inversely related to stock returns, making them capable of offsetting stock market losses in Black Swan events [15, 16]. Given the relative intense nature of the COVID-19 pandemic, information flow in these safe markets is a key element in deciding investor reaction, which would mainly impact the financial sector. Thus, with the COVID-19 pandemic's unparalleled constraints on global financial markets, empirical investigations of these commodities' potential to provide favourable returns to meet portfolio objectives are warranted. A plethora of literature have examined the potentials of safe assets such as gold [13, 17–21], crude oil [22–24], and bitcoin [19, 20, 25, 26]. A similar observation could be made in respect of bonds [27–40]; however, a significant distinction must be noted.

Unlike other safe assets which have a common market, bonds are traded separately in conventional and Islamic markets. So far, studies on bonds have largely focused on the conventional markets with little attention [41–44] on Islamic bonds, a section of the Islamic financial markets (IFMs). Thus, having selected the right asset class is not enough. Another important decision is to choose between conventional and Islamic markets to operate. Islamic assets, which are considered virtue assets, have been introduced and expanded on global financial markets during the past decade. Sharia-compliant assets have grown in popularity not just in Islamic developing countries but also in traditional financial markets. Because they function differently from their conventional equivalents, Sharia-compliant equities and Islamic bonds (Sukuk) are considered innovations in the international financial system. Portfolio risk diversification using Islamic assets would be attractive to investors because of its size, continuous development, and steady performance during and after previous financial crises [45–48].

However, with the daunting nature of the COVID-19 pandemic, which caused a substantial loss (between 30% and 42% of their stock market values) to nearly all of the G7 economies [6], the connectedness of the conventional and Islamic bond markets, which are two distinct asset classes, merits to be revisited in by employing somewhat a novel approach.

As a result, the Baruník and Křehlík [49] (BK-18) methodology is employed to comparatively analyse volatility spillovers between Islamic and conventional bond markets and to assess the dynamism and asymmetries in the connectedness of these markets, contributing to the growing literature on the COVID-19 pandemic and resilience of Islamic markets. In the context of Islamic finance, the study's contribution to the literature on volatility spillover is fourfold. First, the study tackles the disadvantage of analysing composite volatility spillovers across markets, which may conceal important information for fund allocation and risk management. This study accounts for investor heterogeneity (in terms of investment choice and risk appetite) in examining volatility spillovers and the connection network between Islamic and conventional bond markets across the short-, medium-, and long-term periods.

Second, the emotions, expectations, and risk preferences of market participants change over time. Short-term investments appeal to speculators and hedgers, whereas medium-term investments appeal to institutional investors and market regulators. As a consequence, the periodicity-investment component is important for making investment decisions and carrying out long-term objectives. To accomplish so, the study examines how the intricate linkages between Islamic and conventional bond markets have developed over time and at varying frequencies (high, medium, and low). Third, the BK-18 approach, which is based on the Diebold and Yilmaz [50] (DY-12) spillover index's construction, is employed. The DY-12 spillover index, on the other hand, suggests that investors act similarly in markets and that spillover is unaffected by investment horizons, indicating that it is the same in the short-, medium-, and long-term horizons. The study utilises the BK-18 spillover

index, which is based on heterogeneous shock frequency responses, to get past this limitation of the DY-12 approach.

Relative to other approaches (e.g., the GARCH-based methods, transfer entropy, and static and time-domain connectedness approaches), the BK-18 index provides useful information on the magnitudes and directions of spillovers in the time-frequency domain, which is important for identifying the source and magnitude of contagions, as well as the market recipient of shocks. It also examines the volatility connection between markets over time and across various frequencies at the same time. Transfer entropies, GARCH-based models, and spillover approaches that focus on static and time domain only fail to reveal this important information that provides practical insights for market participants. The decomposition into frequencies under the BK-18 approach benefits market participants significantly by separating frequency-domain spillover effects from aggregate risk spillover effects. By differentiating the frequencies, investors may optimise their funding allocation and hedge their position against significant price declines.

Using the BK-18 spillover index, the study finds little evidence of intermittent volatilities for Islamic bonds during the COVID-19 period at high frequencies only, compared to G6 bonds, which showed traces of volatility clusters at all frequencies during the COVID-19 period studied. This finding is suggestive of the relative resilience of Islamic bonds over their conventional counterparts, the G6 bond markets, in the intermediate-to-long-term horizon. More importantly, the findings indicate delayed contagion occurrences based on higher spillovers in 2013, 2016/17, and 2020/21, respectively, owing to the European debt crisis (EDC), the Brexit impact, and the COVID-19 pandemic. USA, Canada, and UK bond markets are the sources of the inferred contagion across all time horizons due to the magnitude of shocks they contribute/transmit across all the bond markets examined. The findings divulge that short-term dynamics play a significant role in spillovers across Islamic bond markets during volatile trading periods, allowing institutional investors to profit from Islamic bonds during market shocks. When G6 bonds are included in a portfolio, speculators and hedgers may concentrate on Islamic bonds only in the medium-to-long term to meet their competitive portfolio objectives.

2. Literature Review

Greater portfolio variety requires a thorough understanding of the interdependencies or contagion (any substantial increase in cross-market connections after a shock in either one nation (market) or a group of nations may cause contagion (markets). The implication is that if there is comovement between two markets during average market conditions, there is interdependence (no contagion) if the comovement between them persists after one of them has experienced a shock; it is only contagion (or "shift-contagion") if a significant increase in an already existing cross-market relationship occurs (Forbes & Rigobon, 2001, 2002). See Forbes and Rigobon (2001, 2002), Ijasan, Owusu Junior, Tweneboah, and Adam (2021), Owusu Junior (2020), Owusu Junior et al. (2020), Owusu Junior, Tweneboah, and Adam (2019), and others for more on contagion.), spillovers, and comovements among the asset classes and markets under consideration.

The methods employed in the extant literature largely suffer from the inability to establish or infer contagion, if any, between these two asset classes. Roukiane and Marzouki [51] compared the dynamics of the volatility of the Sukuk index of various maturities, as well as their conventional counterparts, using a variety of tests, including the Jarque-Bera test, the Granger causality test, Student's *t*-test, and the Ljung-Box test. The authors modelled the behaviour of volatility using the unconditional volatility measured by the monthly standard deviation and the conditional volatility estimated by the generalised autoregressive conditional heteroscedasticity (GARCH) estimator. The study sample consisted of 10 Dow Jones indices of various maturities spanning from January 1, 2014, to April 25, 2017. Roukiane and Marzouki [51] concluded that Sukuks are less risky/volatile than conventional bonds. Akhtar et al. [52] estimated volatility connections, utilising a stochastic volatility model in a Generalised Methods of Moments framework, with additional volatility proxies. After adjusting for the country and asset-specific variables, Akhtar et al. [52] showed that adding at least one Islamic asset reduces volatility correlations by up to 7.17 percentage points and that, during financial crises, the results are better, with no influence from the oil industry. Ghaemi Asl and Rashidi [53] examined the spillover between the MENA stock index and various securities indices, such as Sukuk and conventional bonds, and compared the hedging efficacies of Sukuk and conventional bonds. The authors employed the VAR (1) and multivariate GARCH (1, 1) model to examine the volatility, shock, and asymmetric shock spillover between the Sukuk index and several bond indices in the MENA region.

Ghaemi Asl and Rashidi [53] showed that there is no shock, volatility, or asymmetric shock spillover between the Sukuk index and the MENA stock index, implying that Sukuk indices behave independently from MENA stock indices; however, shock and asymmetric shock spillover exists between MENA stock indices and security indices that include conventional bonds. They show that, throughout both normal and crisis times, the hedging efficacy of Sukuk exhibits consistent patterns. The authors failed to infer contagion from their study. Hkiri et al. [54] used the generalised vector autoregressive method to evaluate the decoupling and contagion hypotheses on the safe haven status of Islamic indices by looking at total, directional, and net volatility spillovers across nine regional Islamic stock indices and their conventional equivalents. The authors utilised daily data from 1999 to 2014, which covers a variety of financial crises, including those in Asia, Russia, Argentina, Brazil, and the United States. They revealed that GFCs have a significant impact on cross-market volatility. The authors further indicated that although the contagion theory holds for both Islamic and conventional indices, their results divulge that, during tumultuous times, Islamic indices decouple from their conventional counterparts. Although

Hkiri et al. [54] had assessed contagion, their study focused on Islamic equities other than bonds.

In the era of the COVID-19 pandemic, studies on financial markets have had diverse methodological paradigms, which either use the time domain (see [55] or the frequency domain only; see also, [46, 47]). Furthermore, the few works on Islamic financial markets also fail to employ methods that consider both time and frequency domains.

Naeem et al. [56] studied the return connectivity in the median, left, and right tails utilising the new quantile-based connectedness approach. Naeem et al. [56] employed daily data between January 2013 and October 2020, which covers several financial crises in the Gulf Cooperation Council, Indonesia, Malaysia, and Turkey. The authors reported that the COVID-19 pandemic has had a substantial impact on the Sukuk market and that the spillover structures in the higher and lower tails vary from those in the intermediate quantile. During the COVID-19 epidemic, Bahrain, Malaysia, Oman, and Qatar are reported by the authors to be higher transmitters of spillovers than they received.

Using the transfer entropy technique, Bossman [46] examined the impact of COVID-19 on Islamic and conventional financial markets, revealing that reported cases of COVID-19 pandemic affect market returns across diverse frequencies. With the same approach, Bossman et al. [47] assessed the stock-bond interrelations between Islamic and conventional markets, concluding that safe haven is applicable to the two asset classes in the studied COVID-19 crisis period. These works focus on the frequency domain with no details about the time domain. Besides, the period is limited to the COVID-19 era, which may not allow for distinguishing interdependence from contagion.

From the extant literature, it could be noticed that a great deal of attention has been offered to composite Islamic market indices with little attention to country-specific prices. Also, to the best of our knowledge, these studies are yet to or failed to employ methods that could infer contagion or stress interdependence among the Islamic and conventional bond markets. Hkiri et al. [54] attempted to analyse contagion but did not employ bonds. The extant research is still divided on whether a spillover is caused by interdependence or contagion (see [57–59], etc.). Furthermore, the COVID-19 pandemic has been blamed for several worldwide economic shocks (see [14, 60, 61], etc.). As a result, investigations of volatility spillovers across and within asset classes must take contagion into account and evaluate its amplitude or severity. The existing literature is yet to address this issue in the context of specific Islamic bond indices. In light of the COVID-19 pandemic, a contribution in this direction is not trivial.

Tiwari et al.'s [62] study employs the spillover methodology but it mainly focuses on green bonds, which may not qualify as a faith-based investment instrument. Aslam et al.'s [63] study focused on financial markets in Europe. Besides, their methodological approach was that of the DY-12, which has limitations that are overcome by the BK-18 spillover approach. Nonetheless, due to the distinct characteristics of IFMs, as mentioned earlier, comparing the connectivity of bonds from Islamic and conventional markets is essential for faith-based investors and regulators. Indicatively, the essence of this study is brought to light when we consider the conclusions from earlier works that assessed the impact of cross-market linkages in systemic crises era like the Brexit [64–66]. The focus of these studies was on conventional markets, with no evidence on how Islamic markets fare during such times and their linkages with their conventional counterparts. This gap is abridged in this study.

The idea that market participants operate on different investment horizons stems mainly from the evolution of investor preferences. This implies that focusing on either the time or frequency domain only is insufficient for horizon-based investors. Consequently, frequency bands that correspond to the short-, medium-, and long-term trading horizons are employed in this study. The use of several GARCH approaches, as held in the literature, and other spillover techniques other than the BK-18 fails to reveal these frequency dynamics. It is instructive to note that this is essential to delineate short-term spillovers from their medium- and long-term ones. Investment decisions hinged on time frequency are of particular importance to speculators who are particularly concerned with short-term gains and institutional investors who may be more interested in long-term cross-market dynamics. Lastly, rather than using aggregated indices for the conventional and Islamic bond markets, this study focuses on country-specific markets to uncover the unique dynamics that may exist in each market and pair of markets. This would provide investors with a more comprehensive view, allowing them to make better and competitive investment choices.

3. Methods and Materials

To uncover the time- and frequency-domain dynamics of the two asset classes under various market circumstances, the study uses the Baruník and Křehlík [49] (BK-18) spillover index to analyse the dynamic connectedness and spillovers between Islamic and conventional bond markets.

3.1. The BK-18 Spillover Index Approach. Baruník and Křehlík [49] used generalised forecast error variance decompositions (GFEVDs) to quantify connectivity, as inspired by Diebold and Yilmaz [50]. The matrix of a vector autoregressive (VAR) model with local covariance stationarity is used to decompose the data. We represent a K-variate procedure, $Y_t = (y_{1,t}, \ldots, y_{K,t})'$, given $t = 1, \ldots, T$ and a VAR(ρ) which may be expressed as

$$Y_t = \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_{t,}. \tag{1}$$

Here coefficient matrices and white noise with (prospective nondiagonal) covariance matrix Π are denoted as ϕ_i and ϵ_i. A regression is carried out between each variable in system (1) and its "own" ρ lags and the ρ lags of all the remaining variables. Accordingly, ϕ holds wide-ranging information on the relationships between all variables. The expediency of working with a $(K \times K)$ matrix $(\mathbf{I}_K - \varnothing_1 L - \ldots - \varnothing_p L^p)$

with identity $\mathbf{I}_K$ must be noted. The VAR system is characterised by a moving average $MA(\infty)$ when the roots of the representative equation $|\theta(z)|$ lie outside of the unit circle.

$$Y_t = \psi(L)\epsilon_t, \tag{2}$$

with $\psi(L)$ depicting an infinitely lagged polynomial. The role of the kth variable, known as the GFEVD, in the variance of forecast error of element j can be written as

$$(\Theta_H)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left((\psi_h\Pi)_{j,k}\right)^2}{\sum_{h=0}^{H}(\psi_h\Pi_{h'})_{j,k}}, \tag{3}$$

where $h = 1, \ldots, H$ and $\sigma_{kk} = (\Pi_{kk})$. This could hold since the measure of connectedness is contingent on decomposed variances, which are the transformations of ψ_h and serve as the contribution of the shocks to the system. Because row contributions do not aggregate to 1, for the sake of completeness, a standardisation of matrix Θ_H is generated as

$$\left(\widetilde{\Theta}_H\right)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N}(\Theta_H)_{j,k}}. \tag{4}$$

The pairwise connectivity (4) may be aggregated for overall connectedness in a system. In line with Diebold and Yilmaz [50], this may be defined as the proportion of variation in predictions provided by errors other than own error (which is the same as the ratio of the off-diagonal components' sum to the whole matrix's sum) as shown in

$$C_H = 100 * \frac{\sum_{j\neq k}\left(\widetilde{\Theta}_H\right)_{j,k}}{\sum\widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\left\{\widetilde{\Theta}_H\right\}}{\sum\widetilde{\Theta}_H}\right), \tag{5}$$

where $Tr\{.\}$ represents the operator for tracing and the arithmetic aggregate of all elements in the matrix is the denominator. As a result, connectedness denotes the forecast variance's relative contribution to the system's other variables. As a result, bidirectional connectivity may be assessed ("to" and/or "from" market i from all other markets k). The difference between "to" and "from" spillovers is also used to calculate "net" connectivity. As a result, a market with a positive net spillover acts as a "net transmitter," while one with a negative spillover acts as a "net receiver" of shocks.

The spectral representation of connectivity is shown at this point. With a frequency response function of $\psi(e)^{-i\omega} = \sum_h e^{-i\omega h}\psi_h$ of coefficients that could be transformed by Fourier transforms ψ_h with $i = \sqrt{-1}$, a spectral density of Y_t at frequency ω can be defined as $MA(\infty)$ filtered series:

$$S_{y(\omega)} = \sum_{h=-\infty}^{\infty} E\left(Y'Y_{t-h}\right)e^{-i\omega h} = \psi\left(e^{-i\omega}\right)\Pi\psi'\left(e^{+i\omega}\right), \tag{6}$$

where $S_{y(\omega)}$ is the power spectrum which details the distribution of the variance of Y_t over the frequency components ω. The causation spectrum over $\omega \in (-\pi, \pi)$ is defined in (7), noting that it reflects the fraction of the ith variable attributable to shocks in the kth variable at a particular frequency ω. As a consequence,

$$(\mathscr{F}(\omega))_{j,k} = \frac{\sigma_{kk}^{-1}\left|\psi\left(e^{-i\omega}\right)\Pi_{j,k}\right|^2}{\left(\psi\left(e^{-i\omega}\right)\Pi\psi'\left(e^{+i\omega}\right)\right)_{j,j}}. \tag{7}$$

It could be understood as within-frequency causation due to the denominator. To get a natural decomposition of GFEVD to frequencies, we weigh $(\mathscr{F}(\omega))_{j,k}$ by the frequency share of the variance of the jth variable. We define the weighting function as

$$\Gamma_j = \frac{\left(\psi\left(e^{-i\omega}\right)\Pi\psi'\left(e^{+i\omega}\right)\right)_{j,j}}{1/2\pi\int_{-\pi}^{\pi}\left(\psi\left(e^{-i\lambda}\right)\Pi\psi'\left(e^{+i\lambda}\right)\right)_{j,j}d\lambda}. \tag{8}$$

It is summated to real-valued (according to Baruník and Křehlík (2018), the generalised causation spectrum is the squared modulus of the weighted complex numbers, resulting in a real-valued quantity) numbers up to 2π and represents the index of the jth variable at a particular frequency. Connectivity must be measured across periods in practical financial applications. As a result, rather than measuring connectedness at single frequencies, it is more appropriate to do so across frequency bands. We take a formal representation of frequency band, d, as $d = (a, b)$: $a, b \in (-\pi, \pi)$, $a < b$, for which we define the GFEVDs as

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)(\mathscr{F}(\omega))_{j,k}d\omega\ . \tag{9}$$

A scaled (As seen in equations (5), (11), and (12), the scaling factor is 100. In the practical application of the connectedness in the BK-18 framework, it is also the minimal forecast horizon H.) generalised variance decomposition may be constructed in the same frequency band d as

$$\left(\widetilde{\Theta}_d\right)_{j,k} = \frac{(\Theta_d)_{j,k}}{\sum_k(\Theta_\infty)_{j,k}}. \tag{10}$$

Then, the within-frequency and frequency connectivity across d are expressed in (11) and (12), respectively.

$$C_d^W = 100.\left(1 - \frac{Tr\left\{\widetilde{\Theta}_d\right\}}{\sum\widetilde{\Theta}_d}\right). \tag{11}$$

$$C_d^F = 100.\left(\frac{\sum\widetilde{\Theta}_d}{\sum\widetilde{\Theta}_\infty} - \frac{Tr\left\{\widetilde{\Theta}_d\right\}}{\sum\widetilde{\Theta}_\infty}\right) = C_d^W.\left(\frac{\sum\widetilde{\Theta}_d}{\sum\widetilde{\Theta}_\infty}\right). \tag{12}$$

It is important to note that C_d^W represents the connectivity that occurs inside a frequency band and is only weighted by the series' power on that frequency band. C_d^F, on the other hand, breaks down overall connectivity into discrete pieces that add up to the original connectedness metric, as presented by Baruník and Křehlík [49]. ($\pi + 0.00001$, $\pi/4$, $\pi/16$, $\pi/32$, $\pi/64$, 0) are the frequency bands we utilise, which is in line with Baruník and Křehlík [49], Tiwari et al. [67], Tiwari et al. [68], Owusu Junior [57], and Owusu Junior et al. [58]. Table 1 shows the daily ranges that correspond to the relevant bands.

Table 1: Interpretations to frequency bands.

Frequency	Bands	Days	Interpretation
d_1	3.14 ~ 0.79	1 ~ 4	Intraweek
d_2	0.79 ~ 0.20	4 ~ 16	Week-to-fortnight
d_3	0.20 ~ 0.10	16 ~ 32	Fortnight-to-month
d_4	0.10 ~ 0.05	32 ~ 64	Month-to-quarter
d_5	0.05 ~ 0.00	64 ~ ∞	Quarter-and-beyond

3.2. Data. The daily bond yield market indices for five key Islamic bond markets (India, Indonesia, Malaysia, Pakistan, and Qatar) and G6 (G6 instead of G7 because the bond yield for Germany had been negative since 22 March 2019, making it impracticable to compute log returns over the COVID-19 period. For unbiased estimates, Germany was, therefore, eliminated from the studied countries.) economies (Canada, France, Italy, Japan, UK, and USA) (in ascending order per country spellings) with available data were utilised in the study. The data set spanned between 22 August 2012 and 17 September 2021, yielding 1272 common data observations. The daily 10-year bond indices were supplied by EquityRT and are expressed in USD. The log-returns of the daily bond indices were computed as follows:

$$r_t = lnP_t - lnP_{t-1}. \tag{13}$$

In the above equation, r_t defines the continuously compounded returns, P_t represents the price of an asset (bond) in period t, and P_{t-1} represents the price of the asset in the previous period $t-1$.

A forecast horizon (H) of 100 days is utilised, as well as a 100-day rolling window. This aggregates to a little over a quarter of a year, and it is sufficient to accommodate for time differences in the bond markets. The rolling window framework eliminates the need for crisis start and end dates to be specified exogenously. By displaying the resultant spillover indices, we can account for significant changes in the form of spillovers throughout the sample period, as advocated by Yilmaz [69], Owusu Junior [57], and Owusu Junior et al. [58].

A trajectory of the bond yield indices for all the countries is presented in Figure 1. The Shapiro-Wilk test of normalcy confirms skewness and excess kurtosis (see Table 2). The resulting statistics for skewness and kurtosis, respectively, depict nonnormal and leptokurtic distributions across the markets studied. Asymmetries in return distributions are confirmed by these findings, offering a strong incentive to use the BK-18 approach, relative to the DY-12 time-invariant approach, to examine the dynamic and asymmetric connection between Islamic and conventional bonds. Traces of volatilities may also be seen in the time series returns plots in Figure 2, indicating that the series is generating time-varying risk.

The mean returns on bond yield over the entire sample were positive for all Islamic countries except for Qatar, even though it is almost zero. For all G6 bond yield markets, the mean returns over the studied period were negative but close to zero. An important revelation is made by the time series plots. We find the "Brexit effect" (We refer to the Brexit effect as the substantial losses borne by global investors on 24 June 2016 following the referendum that confirmed Britain's exit (Brexit) from the European Union (David, 2016). The Brexit caused investors in global stock markets to lose over US$2 trillion, making it the biggest single-day loss in history.) in 2016/17 where almost all the bond yield indices studied experienced a sharp drop followed by a sharp rise in the yields. This finding is consistent with the empirical literature that found that cross-market linkages were affected as a result of the Brexit referendum [64–66].

4. Results

4.1. Time-Frequency-Domain Analysis. By accounting for the development of total connection across time, the time-frequency-domain approach aids in determining whether or not there is contagion. We proceed by examining the impact of spillovers between the Islamic and G6 bond markets at different frequencies, which result from the decomposition of the data series. This decomposition tries to account for market players' various expectations and desires across various time periods. Tables 3–5 show the short-, medium-, and intermediate-term spillovers in the markets under study, classified into five frequency bands (intraweek, week-to-fortnight, fortnight-to-month, month to quarter, and quarter and beyond), respectively, for Islamic and G6 bond markets, Islamic only, and G6 only. The tables and plots of the pairwise net spillover effects between Islamic and G6 bonds, Islamic bonds alone, and G6 bonds are not presented here for want of space (These are available upon request to the corresponding author.).

The spillover effects for all markets (Islamic and G6) in Table 3 show that spillovers are relatively greater in the very short-term (intraweek) than in the medium-to long-term timeframes. For instance, the return spillover within the first band, 3.14 ~ 0.79, which approximates to 1 ~ 4 days is 18.76%. This return spillover reduces to 6.03%, 1.4%, 0.71%, and 0.35% in respect of the second (0.79 ~ 0.20), third (0.20 ~ 0.10), fourth (0.10 ~ 0.05), and fifth (0.05 ~ 0.00) bands, respectively, and corresponds to intraweek, week-to-fortnight, fortnight-to-month, month to quarter, and quarter and beyond, respectively. Similarly, the spillover is seen to be decreasing over time both among Islamic bonds only and among G6 bond markets only, with the volatilities in G6 bonds exhibiting high magnitudes. This result suggests that, in the initial few trading days, all bond markets react rapidly to shocks. The Islamic and G6 markets examined are, at best, more sensitive to market shocks within the intraweek band (3.14 ~ 0.79) during the studied period.

Note: (a) "Absolute to" measures return spillovers from market/country j to other markets. "Absolute from" measures return spillovers from other markets to market j. (b) Within to measures return spillovers from market j to other markets, including from own innovations to country k. Within from measures return spillovers from other markets to market j, including from own innovations to market k (see [57, 58, 67, 68]). The largest contributions of markets per frequency band are in bold italics. A positive "Net"

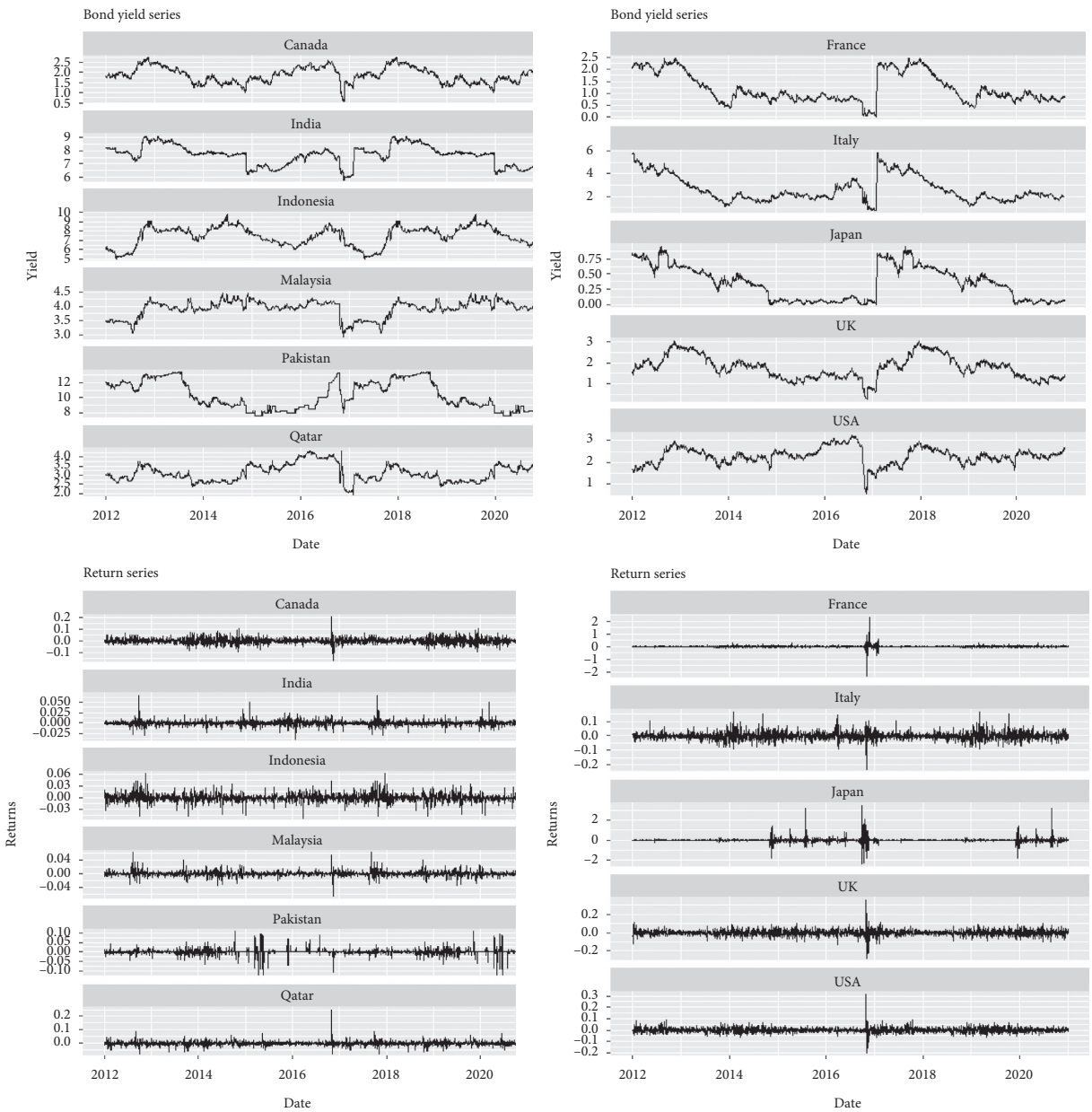
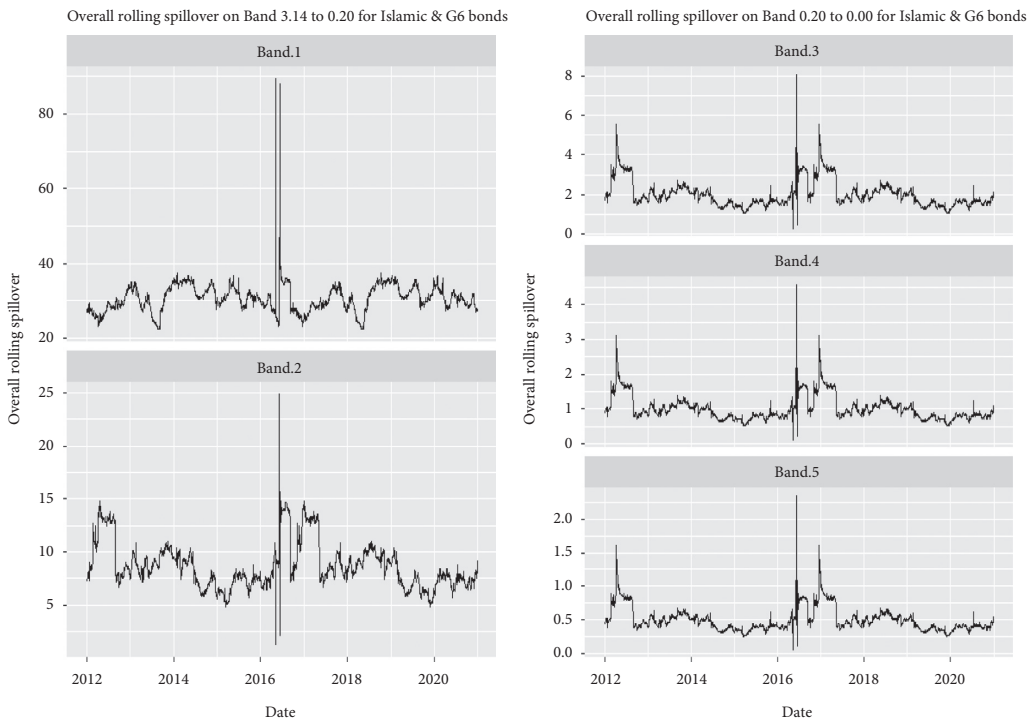


Figure 1: Time series plots of bond yield indices and returns for Islamic and G6 markets.

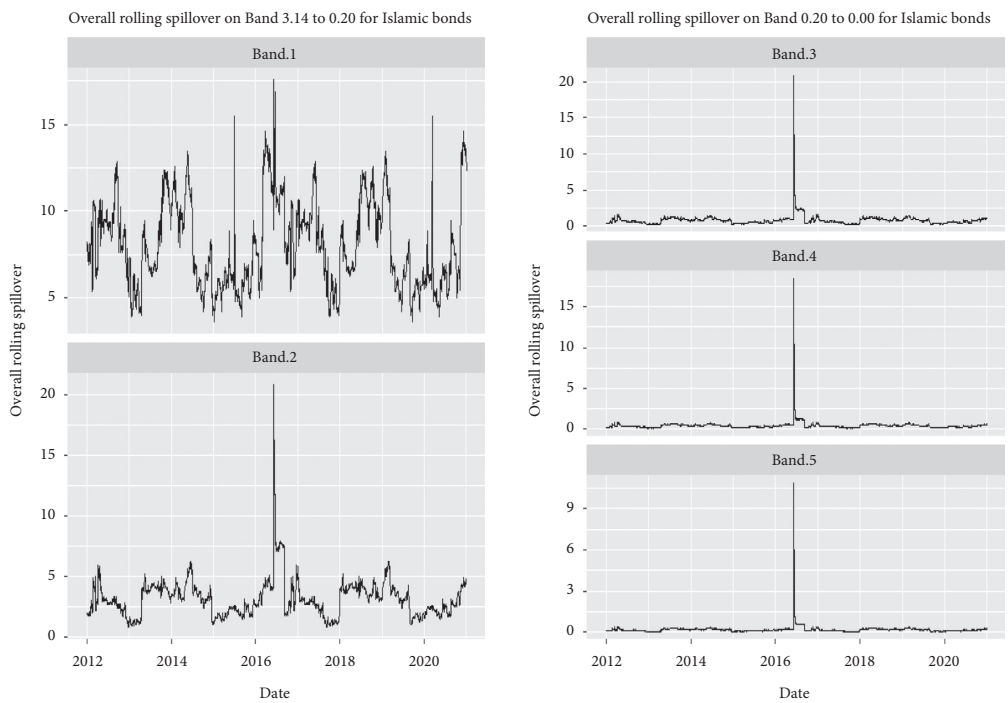
Table 2: Descriptive summary.

Islamic	India	Indonesia	Malaysia	Pakistan	Qatar	
Observations	1272	1272	1272	1272	1272	
Mean	0.0001	0.0006	0.0001	0.0001	−0.0001	
Std. dev	0.0063	0.0099	0.0074	0.0145	0.0161	
Skewness	1.1291	0.1774	0.401	−0.3095	3.3397	
Kurtosis	15.4656	4.6015	15.2639	24.8583	51.5892	
Normtest.W*	0.8707	0.9352	0.8257	0.5507	0.7767	
G6	Canada	France	Italy	Japan	UK	USA
Observations	1272	1272	1272	1272	1272	1272
Mean	−0.001	−0.0012	−0.0011	−0.0014	−0.0006	−0.0003
Std. dev	0.0244	0.127	0.0286	0.2663	0.0349	0.0241
Skewness	0.3292	0.6811	−0.1962	2.2319	0.3779	1.8045
Kurtosis	7.0369	178.9996	9.7366	57.6261	16.9531	34.547
Normtest.W*	0.9457	0.366	0.915	0.4834	0.8751	0.826

*estimates are significant at the 1% level of significance.



(a)



(b)

Figure 2: Continued.

(c)

Figure 2: Overall rolling spillovers across time horizons. (a) Panel A: Islamic and G6 bond markets. (b) Panel B: Islamic bond markets. (c) Panel C: G6 bond markets.

suggests that the country/market is a net transmitter, while a negative "Net" denotes net recipient market/country.

These results are consistent with the EMH such that, in the short term, asset prices fully reflect all pertinent information [9, 10], resulting in high market dynamics at high frequencies. Mensi et al. [24] used a similar approach to find that short-term spillovers have relative importance over intermediate-term spillovers for Islamic and conventional markets, particularly BRICS countries. These findings contrast with those of Hassan et al. [70] who used TGARCH and GFEVD to calculate time- and frequency-domain volatility spillover for Islamic and conventional financial markets but found that the overall volatility spillover is primarily driven by a long-term component and, as a result, suggested that investors with short- and medium-term investment goals consider these assets.

When the chosen Islamic and G6 economies are examined jointly, USA (4.71%), UK (4.36%), and Canada (3.83%) are the biggest contributors of shocks to the studied markets at the high frequency (short term) spillover band. These economies continue to be the principal transmitters of shocks in all other spillover bands, with the exception that the size of spillovers transmitted by Canada surpasses that of UK in the remaining spillover bands. Pakistan, on the other hand, is the lowest contributor to the shocks between the bond markets examined across all spillover bands. This means that the Pakistani bond market is less susceptible to shocks than other traditional bond markets, making it a good choice for diversification amid market stress. Following that, we isolate the two main markets to investigate the transmission of volatility between and within them. From the Islamic bond markets alone, we discovered that Malaysia and Qatar contribute the most to bond market return spillovers across all frequency domains, whereas Pakistan contributes the least. USA, Canada, and UK were shown to be the major sources of volatility spillovers throughout the G6 markets. Japan, on the other hand, was determined to provide a little amount of volatility spillover to the G6 markets. In comparison, we find that the G6 bond markets have higher magnitudes of volatility across all time periods than the Islamic bond markets. The findings confirm Roukiane and Marzouki's [51] conclusion that Islamic bonds are less risky/volatile than conventional bonds.

The results show that USA gets the greatest degree of volatility spillover in the short term, particularly in the spillover range of 3.14 to 0.79, after examining the markets collectively in terms of receivers of bond market return volatilities. UK receives the most volatility spillover between the chosen Islamic and G6 bond markets between bands 2 and 5. Across all spillover bands, Pakistan's bond market admits the fewest spillovers from its Islamic and G6 counterparts. When the two wide bond markets are examined separately, Malaysia suffers the most volatility spillovers from other Islamic bond markets in the spillover range of 3.14 ~ 0.79, while Indonesia receives the most volatility spillovers in bands 2 to 5. The Pakistani bond market has the fewest volatility spillovers from its Islamic counterparts across all frequency domains. Canada has the most volatility spillover in the G6 markets in the very short term (3.14 ~ 0.79), whereas UK has the most volatility

Table 3: Total and Net spillover indices across frequency bands for Islamic and G6 bonds.

	India	Indonesia	Malaysia	Pakistan	Qatar	Canada	France	Italy	Japan	UK	USA	FROM_ABS(a)	FROM_WTH(b)
Spillover band: 3.14 to 0.79; corresponds to 1 day to 4 days (intraweek)													
India	71.07	0.75	0.78	0.06	1.11	0.23	0.09	0.06	0.08	0.22	0.37	0.34	0.46
Indonesia	0.4	57.04	2.01	0.16	1.17	0.1	0.03	0.18	0.06	0.21	0.18	0.41	0.56
Malaysia	0.51	1.6	49.45	0.11	1.47	1.39	1.27	0.65	0.07	0.91	2.51	0.95	1.3
Pakistan	0.02	0.05	0.25	82.8	0.04	0.07	0.4	0.27	0.03	0.4	0.05	0.14	0.19
Qatar	0.6	0.66	0.8	0.19	52.36	2.05	1.71	0.1	0.74	2.65	4.03	1.23	1.68
Canada	0.03	0.03	0.23	0.09	0.76	33.73	2.77	0.77	0.36	13.08	22.27	3.67	5.01
France	0.05	0.02	1.25	0.06	1.61	3.29	52.87	6.01	0.74	10.72	4.59	2.58	3.52
Italy	0.03	0.01	0.26	0.38	0.27	1.43	9.16	59.45	0.23	3.6	1.34	1.52	2.07
Japan	0.19	0.07	0.08	0.01	0.85	1.16	1.27	0.54	74.18	1.39	1.68	0.66	0.9
UK	0.02	0.08	0.29	0.28	1.9	12.11	7.55	1.35	0.77	34.86	14.76	3.56	4.85
USA	0.02	0.02	0.44	0.02	1.06	20.36	2.87	0.44	0.7	14.81	31.83	3.7	5.05
TO_ABS(a)	0.17	0.3	0.58	0.12	0.93	3.83	2.47	0.94	0.34	4.36	4.71	18.76	
TO_WTH(b)	0.23	0.41	0.79	0.17	1.27	5.23	3.37	1.29	0.47	5.95	6.42		25.6
Net	−0.169	−0.110	−0.372	−0.020	−0.299	0.162	−0.110	−0.578	−0.314	0.806	1.003		
Spillover band: 0.79 to 0.20; corresponds to 4 days to 16 days (week-to-a-fortnight)													
India	16.88	0.06	0.12	0	0.61	0.19	0.01	0.01	0.03	0.05	0.2	0.12	0.61
Indonesia	0.36	22.03	2.13	0.12	1.34	0.25	0.04	0.18	0.04	0.07	0.35	0.44	2.32
Malaysia	0.46	1.01	19.02	0.08	1.14	1.49	0.74	0.49	0.02	1.03	2.55	0.82	4.28
Pakistan	0	0.01	0.02	11.03	0	0.01	0.12	0.13	0	0.01	0.02	0.03	0.16
Qatar	0.19	0.26	0.63	0.02	14.55	2.08	0.42	0.13	0.19	2.3	3.38	0.87	4.57
Canada	0.01	0.01	0.03	0.01	0.15	8.96	0.24	0.16	0.04	3.27	5.69	0.87	4.57
France	0.01	0	0.26	0.02	0.33	0.46	9.22	1.73	0.23	0.85	0.49	0.4	2.09
Italy	0	0	0.03	0.01	0.01	0.26	1.31	15.32	0.01	0.24	0.09	0.18	0.93
Japan	0.01	0	0.03	0	0.32	0.65	0.43	0.22	10.3	0.66	0.87	0.29	1.52
UK	0	0	0.03	0	0.17	4.68	0.6	0.33	0.04	7.59	5.31	1.02	5.32
USA	0.01	0	0.08	0	0.14	6.26	0.42	0.19	0.03	3.83	8.8	1	5.21
TO_ABS(a)	0.1	0.12	0.31	0.02	0.38	1.48	0.39	0.32	0.06	1.12	1.72	6.03	
TO_WTH(b)	0.51	0.65	1.6	0.13	2	7.77	2.06	1.7	0.3	5.85	9.02		31.59
Net	−0.020	−0.319	−0.513	−0.006	−0.491	0.611	−0.006	0.146	−0.233	0.103	0.727		
Spillover band: 0.20 to 0.10; corresponds to 16 days to 32 days (fortnight-to-month)													
India	3.74	0.01	0.02	0	0.14	0.05	0	0	0.01	0.01	0.05	0.03	0.59
Indonesia	0.1	5.27	0.57	0.03	0.36	0.08	0.01	0.05	0.01	0.01	0.1	0.12	2.73
Malaysia	0.12	0.25	4.54	0.02	0.28	0.39	0.18	0.12	0	0.27	0.67	0.21	4.82
Pakistan	0	0	0	2.37	0	0	0.03	0.03	0	0	0	0.01	0.15
Qatar	0.05	0.06	0.15	0	3.29	0.53	0.09	0.03	0.04	0.57	0.84	0.22	4.96
Canada	0	0	0.01	0	0.03	2.03	0.04	0.03	0.01	0.74	1.28	0.2	4.49
France	0	0	0.06	0	0.08	0.09	2.02	0.39	0.05	0.17	0.1	0.09	1.98
Italy	0	0	0	0	0	0.04	0.27	3.39	0	0.03	0	0.03	0.76
Japan	0	0	0.01	0	0.07	0.15	0.09	0.05	2.19	0.15	0.2	0.07	1.51
UK	0	0	0	0	0.03	1.06	0.11	0.07	0.01	1.68	1.19	0.23	5.17
USA	0	0	0.02	0	0.03	1.41	0.08	0.04	0	0.85	1.96	0.22	5.08

Table 3: Continued.

	India	Indonesia	Malaysia	Pakistan	Qatar	Canada	France	Italy	Japan	UK	USA	FROM_ABS(a)	FROM_WTH(b)
TO_ABS(a)	0.03	0.03	0.08	0.01	0.09	0.35	0.08	0.08	0.01	0.26	0.4	1.4	
TO_WTH(b)	0.58	0.68	1.76	0.14	2.11	7.96	1.89	1.72	0.27	5.87	9.26		32.23
Net	−0.000	−0.089	−0.134	−0.001	−0.124	0.151	−0.004	0.042	−0.054	0.030	0.182		
Spillover band: 0.10 to 0.05; corresponds to 32 days to 64 days (month-to-quarter)													
India	1.87	0	0.01	0	0.07	0.02	0	0	0	0	0.02	0.01	0.59
Indonesia	0.05	2.65	0.29	0.02	0.18	0.04	0.01	0.03	0	0	0.05	0.06	2.77
Malaysia	0.06	0.13	2.29	0.01	0.14	0.2	0.09	0.06	0	0.14	0.34	0.11	4.88
Pakistan	0	0	0	1.18	0	0	0.01	0.01	0	0	0	0	0.15
Qatar	0.03	0.03	0.08	0	1.65	0.27	0.05	0.02	0.02	0.29	0.42	0.11	4.99
Canada	0	0	0	0	0.02	1.01	0.02	0.02	0	0.37	0.64	0.1	4.48
France	0	0	0.03	0	0.04	0.05	1.01	0.2	0.03	0.08	0.05	0.04	1.97
Italy	0	0	0	0	0	0.02	0.13	1.69	0	0.02	0	0.02	0.74
Japan	0	0	0	0	0.04	0.08	0.05	0.02	1.09	0.08	0.1	0.03	1.5
UK	0	0	0	0	0.01	0.53	0.05	0.04	0	0.84	0.6	0.11	5.16
USA	0	0	0.01	0	0.01	0.71	0.04	0.02	0	0.43	0.98	0.11	5.07
TO_ABS(a)	0.01	0.01	0.04	0	0.05	0.17	0.04	0.04	0.01	0.13	0.2	0.71	
TO_WTH(b)	0.58	0.68	1.77	0.14	2.12	7.97	1.87	1.73	0.27	5.87	9.28		32.29
Net	0.000	−0.046	−0.068	0.00	−0.063	0.076	−0.002	0.022	−0.027	0.016	0.092		
Spillover band: 0.05 to 0.00; corresponds to 64 days to infinite days (quarter and beyond)													
India	0.94	0	0.01	0	0.03	0.01	0	0	0	0	0.01	0.01	0.58
Indonesia	0.02	1.33	0.14	0.01	0.09	0.02	0	0.01	0	0	0.03	0.03	2.78
Malaysia	0.03	0.06	1.14	0.01	0.07	0.1	0.04	0.03	0	0.07	0.17	0.05	4.89
Pakistan	0	0	0	0.59	0	0	0.01	0.01	0	0	0	0	0.15
Qatar	0.01	0.02	0.04	0	0.83	0.13	0.02	0.01	0.01	0.15	0.21	0.05	5
Canada	0	0	0	0	0.01	0.51	0.01	0.01	0	0.19	0.32	0.05	4.48
France	0	0	0.01	0	0.02	0.02	0.5	0.1	0.01	0.04	0.02	0.02	1.97
Italy	0	0	0	0	0	0.01	0.07	0.85	0	0.01	0	0.01	0.74
Japan	0	0	0	0	0.02	0.04	0.02	0.01	0.54	0.04	0.05	0.02	1.5
UK	0	0	0	0	0.01	0.27	0.03	0.02	0	0.42	0.3	0.06	5.15
USA	0	0	0	0	0.01	0.35	0.02	0.01	0	0.21	0.49	0.06	5.06
TO_ABS(a)	0.01	0.01	0.02	0	0.02	0.09	0.02	0.02	0	0.06	0.1	0.35	
TO_WTH(b)	0.59	0.68	1.78	0.14	2.13	7.98	1.87	1.73	0.27	5.87	9.28		32.3
Net	0.000	−0.023	−0.034	0.000	−0.031	0.038	−0.001	0.011	−0.013	0.008	0.046		

Note: (a) "Absolute to" measures return spillovers from market/country j to other markets. "Absolute from" measures return spillovers from other markets to market j. (b) Within to measures return spillovers from market j to other markets, including from own innovations to country k. Within from measures return spillovers from other markets to market j, including from own innovations to market k (see [57, 58, 67, 68]). The largest contributions of markets per frequency band are in bold italics. A positive "Net" suggests that the country/market is a net transmitter, while a negative "Net" denotes net recipient market/country.

Table 4: Total and Net spillover indices across frequency bands for Islamic bonds.

	India	Indonesia	Malaysia	Pakistan	Qatar	FROM_ABS(a)	FROM_WTH(b)
Spillover band: 3.14 to 0.79; corresponds to 1 day to 4 days (intraweek)							
India	71.7	0.8	1.01	0.06	1.31	0.64	0.9
Indonesia	0.45	57.51	2.17	0.17	1.27	0.81	1.15
Malaysia	0.79	1.92	56.79	0.11	2.1	0.98	1.4
Pakistan	0.03	0.04	0.19	84.31	0.03	0.06	0.08
Qatar	1.02	0.86	1.55	0.18	65.93	0.72	1.03
TO_ABS(a)	0.46	0.72	0.98	0.11	0.94	3.21	
TO_WTH(b)	0.65	1.03	1.4	0.15	1.34		4.56
Net	−0.178	−0.087	0.00	0.047	0.219		
Spillover band: 0.79 to 0.20; corresponds to 4 days to 16 days (week-to-a-fortnight)							
India	17.06	0.07	0.18	0	0.78	0.21	0.99
Indonesia	0.39	22.35	2.41	0.11	1.55	0.89	4.27
Malaysia	0.62	1.23	22.6	0.07	2.14	0.81	3.89
Pakistan	0	0.01	0.02	11.17	0	0.01	0.04
Qatar	0.33	0.34	1.38	0.03	19.46	0.41	1.98
TO_ABS(a)	0.27	0.33	0.8	0.04	0.9	2.33	
TO_WTH(b)	1.29	1.58	3.83	0.2	4.29		11.18
Net	0.061	−0.563	−0.014	0.034	0.482		
Spillover band: 0.20 to 0.10; corresponds to 16 days to 32 days (fortnight-to-month)							
India	3.78	0.01	0.04	0	0.18	0.05	0.94
Indonesia	0.11	5.39	0.66	0.03	0.43	0.25	4.96
Malaysia	0.16	0.32	5.55	0.02	0.57	0.21	4.3
Pakistan	0	0	0.01	2.39	0	0	0.04
Qatar	0.08	0.08	0.36	0.01	4.56	0.11	2.15
TO_ABS(a)	0.07	0.08	0.21	0.01	0.24	0.61	
TO_WTH(b)	1.41	1.67	4.32	0.21	4.77		12.38
Net	0.023	−0.162	0.001	0.009	0.129		
Spillover band: 0.10 to 0.05; corresponds to 32 days to 64 days (month-to-quarter)							
India	1.89	0	0.02	0	0.09	0.02	0.93
Indonesia	0.05	2.71	0.34	0.01	0.22	0.13	5.03
Malaysia	0.08	0.16	2.8	0.01	0.29	0.11	4.34
Pakistan	0	0	0	1.19	0	0	0.04
Qatar	0.04	0.04	0.18	0	2.29	0.05	2.17
TO_ABS(a)	0.04	0.04	0.11	0.01	0.12	0.31	
TO_WTH(b)	1.42	1.68	4.37	0.22	4.81		12.5
Net	0.012	−0.083	0.001	0.004	0.066		
Spillover band: 0.05 to 0.00; corresponds to 64 days to infinite days (quarter and beyond)							
India	0.95	0	0.01	0	0.05	0.01	0.93
Indonesia	0.03	1.36	0.17	0.01	0.11	0.06	5.04
Malaysia	0.04	0.08	1.4	0	0.15	0.05	4.35
Pakistan	0	0	0	0.59	0	0	0.04
Qatar	0.02	0.02	0.09	0	1.15	0.03	2.17
TO_ABS(a)	0.02	0.02	0.05	0	0.06	0.16	
TO_WTH(b)	1.42	1.68	4.38	0.22	4.82		12.52
Net	0.006	−0.042	0.000	0.00	0.033		

Note: (a) "Absolute to" measures return spillovers from market/country j to other markets. "Absolute from" measures return spillovers from other markets to market j. (b) Within to measures return spillovers from market j to other markets, including from own innovations to country k. Within from measures return spillovers from other markets to market j, including from own innovations to market k (see [57, 58, 67, 68]). The largest contributions of markets per frequency band are in bold italics. A positive "Net" suggests that the country/market is a net transmitter, while a negative "Net" denotes net recipient market/country.

spillovers in bands 2 to 5 (0.79 ~ 0.00). Japan (Italy) acknowledges the fewest short-term (intermediate to long term) volatility spillovers from its counterparts among the G6 bond markets.

Evaluations of the findings are presented in Tables 3–5, which show the markets' net transmitters and receivers of bond return volatilities. The findings indicate that Canada, USA, and UK are the net transmitters of spillovers between the Islamic and G6 economies in the near run, within the spillover band of 3.14 ~ 0.79. All of the Islamic markets, as well as the other G6 markets, were shown to be net shock receivers. Pakistan and Qatar (India, Indonesia, and

Table 5: Total and Net spillover indices across frequency bands for G6 bonds.

	Canada	France	Italy	Japan	UK	USA	FROM_ABS(a)	FROM_WTH(b)
Spillover band: 3.14 to 0.79; corresponds to 1 day to 4 days (intraweek)								
Canada	34.26	2.78	0.79	0.37	13.25	22.59	6.63	8.69
France	3.43	55.32	6.22	0.79	11.01	4.78	4.37	5.73
Italy	1.43	9.06	59.87	0.25	3.71	1.34	2.63	3.45
Japan	1.26	1.28	0.54	75.3	1.53	1.87	1.08	1.42
UK	12.3	7.62	1.4	0.77	35.84	14.94	6.17	8.08
USA	20.67	2.87	0.45	0.72	15.03	32.33	6.62	8.68
TO_ABS(a)	6.52	3.94	1.57	0.48	7.42	7.59	27.51	
TO_WTH(b)	8.54	5.16	2.05	0.63	9.72	9.94		36.04
Net	−0.115	−0.434	−1.066	−0.599	1.252	0.962		
Spillover band: 0.79 to 0.20; corresponds to 4 days to 16 days (week-to-a-fortnight)								
Canada	9.08	0.24	0.16	0.04	3.31	5.76	1.59	9.31
France	0.47	9.58	1.76	0.24	0.86	0.5	0.64	3.75
Italy	0.28	1.34	15.61	0.01	0.25	0.08	0.33	1.91
Japan	0.63	0.43	0.22	10.51	0.62	0.83	0.45	2.66
UK	4.89	0.62	0.37	0.04	7.91	5.59	1.92	11.25
USA	6.4	0.42	0.2	0.03	3.92	9.03	1.83	10.75
TO_ABS(a)	2.11	0.51	0.45	0.06	1.49	2.13	6.75	
TO_WTH(b)	12.38	2.99	2.65	0.36	8.77	12.48		39.62
Net	0.523	−0.13	0.127	−0.392	−0.423	0.296		
Spillover band: 0.20 to 0.10; corresponds to 16 days to 32 days (fortnight-to-month)								
Canada	2.06	0.05	0.04	0.01	0.75	1.3	0.36	9.42
France	0.09	2.09	0.4	0.05	0.16	0.09	0.13	3.48
Italy	0.05	0.28	3.49	0	0.04	0.01	0.06	1.71
Japan	0.14	0.09	0.05	2.24	0.14	0.19	0.1	2.71
UK	1.13	0.12	0.08	0.01	1.78	1.29	0.44	11.55
USA	1.46	0.09	0.05	0	0.89	2.03	0.41	10.92
TO_ABS(a)	0.48	0.1	0.1	0.01	0.33	0.48	1.51	
TO_WTH(b)	12.66	2.77	2.68	0.33	8.7	12.64		39.79
Net	0.123	−0.027	0.037	−0.09	−0.108	0.065		
Spillover band: 0.10 to 0.05; corresponds to 32 days to 64 days (month-to-quarter)								
Canada	1.03	0.02	0.02	0	0.38	0.65	0.18	9.43
France	0.04	1.04	0.2	0.03	0.08	0.04	0.07	3.46
Italy	0.03	0.14	1.74	0	0.02	0	0.03	1.69
Japan	0.07	0.05	0.03	1.12	0.07	0.09	0.05	2.71
UK	0.57	0.06	0.04	0	0.89	0.65	0.22	11.58
USA	0.73	0.04	0.02	0	0.44	1.02	0.21	10.94
TO_ABS(a)	0.24	0.05	0.05	0.01	0.16	0.24	0.75	
TO_WTH(b)	12.69	2.75	2.69	0.33	8.7	12.65		39.81
Net	0.062	−0.013	0.019	−0.045	−0.055	0.033		
Spillover band: 0.05 to 0.00; corresponds to 64 days to infinite days (quarter and beyond)								
Canada	0.51	0.01	0.01	0	0.19	0.33	0.09	9.43
France	0.02	0.52	0.1	0.01	0.04	0.02	0.03	3.45
Italy	0.01	0.07	0.87	0	0.01	0	0.02	1.69
Japan	0.04	0.02	0.01	0.56	0.03	0.05	0.03	2.71
UK	0.28	0.03	0.02	0	0.45	0.32	0.11	11.58
USA	0.37	0.02	0.01	0	0.22	0.51	0.1	10.94
TO_ABS(a)	0.12	0.03	0.03	0	0.08	0.12	0.38	
TO_WTH(b)	12.69	2.75	2.69	0.33	8.7	12.66		39.81
Net	0.031	−0.007	0.009	−0.023	−0.027	0.016		

Malaysia) were shown to be net transmitters (recipients) of high-frequency shocks to the examined Islamic bond markets. Except for Indonesia, all other markets between bands 2 and 5 were net spillover broadcasters. Across all frequency bands, Indonesia was shown to be a constant net receiver of shocks from its equivalent Islamic bond markets. Canada, UK, and USA (France and Japan) were net transmitters (recipients) of spillovers across all frequency bands in the G6 bond markets. Italy was discovered to be a net receiver of shocks in the high-frequency range (short term) but not in the intermediate to long term. The results indicate that volatility spillovers between and within Islamic

and/or G6 bond markets are time- and frequency-dependent, which is in line with the HMH [12]. Mensi et al. [24] came to the same result, revealing that volatility spillovers between Islamic and conventional markets, from the BRICS countries, were dependent on time scales and frequencies. Investors who keep assets in traditional markets in pursuit of competitive returns are likely to adapt to Islamic bonds in difficult times, according to this finding, which is consistent with the AMH and CMH of Lo [11] and Owusu Junior et al. [14], respectively. This observation corroborates Akhtar et al.'s [52] conclusion that adding at least one Islamic asset significantly reduces volatility correlations during financial crises.

Figure 2 depicts the return volatility of Islamic and G6 bond markets over time. Panel A depicts the time-frequency dynamics of return volatility for both Islamic and G6 bonds, whereas Panels B and C depict the return volatility of Islamic and G6 bonds, respectively.

The volatility spillovers are dominant in the short term for all samples, according to the plots. Across the frequency bands, we have a similar pattern of spillovers with varying magnitudes. We see fluctuations in spillover in Panel A (the all-markets sample), but they are mostly between 25% and 35% in the short term, with an increase to almost 90% by 2017. Volatility spillover clusters are observable for all markets across all time periods, but they vary when the markets are examined individually. We see a reasonably stable pattern of spillovers between 2018 and 2020. Around 2021, there was a marginal increase in spillovers between the two wide bond markets, Islamic and G6. In contrast to Islamic bonds, a separate study of the two bond markets shows that G6 bonds are prone to high volatility spillovers. We find that, in the short term (in the spillover band 1), spillovers across Islamic bond markets are largely between 5% and 15%, which, despite their lower magnitude, appear to be more volatile than spillovers across G6 bond markets, which are instead high in magnitudes ranging between 25% and 45% over the studied period. For the two distinct markets, a similar observation is made in band 2 (0.79 ~ 0.20, representing week-to-fortnight). With Islamic bonds, we have a stable pattern and modest magnitudes of volatilities in bands 3 to 5 (intermediate to long term), while, with G6 bond markets, we see significantly higher volatilities.

In the intermediate to long term, our findings indicate that conventional bonds are more volatile than Islamic equities. These results are consistent with the findings of Roukiane and Marzouki [51] who concluded that Islamic bonds exhibit fewer volatilities than conventional bonds. Similarly, the findings are consistent with the observations made by Hkiri et al. [54] that Islamic indices disconnect from their conventional equivalents during turbulent periods. Apart from providing support for our findings, the plots (Figure 2) demonstrate that the results are similar to those presented in Tables 3–5. Across all frequencies, we find minimal evidence of sporadic volatilities for Islamic bonds during the COVID-19 era. Although Islamic bond markets had plenty of volatility clusters in the short term (bands 1 and 2), there was no indication of prolonged volatility during COVID-19. Despite the relatively low volatility clusters in bands 1 and 2, we detect occasional volatility spillovers across all frequencies in the G6 bond markets throughout the COVID-19 pandemic period.

Furthermore, by inference, we find contagion across all spillover bands on three occasions. The first is spotted in 2016/2017 (see Figure 2). Notably, our findings show the evolution of contagion in 2017, with significant increases in spillover connectivity between the investigated Islamic and G6 bond markets, corroborating Forbes and Rigobon's [71, 72] definition of contagion. We see rising volatilities (almost 90%) for all markets at high frequencies (in the near term), which decreases through spillover bands 2–4. According to Mensi et al. [24], this contagion may be attributed to China's economic downturn in 2017 and/or global investors' significant losses on June 24, 2016, after the vote that confirmed Britain's exit from the European Union [73]. Global stock markets lost nearly US$2 trillion as a result of the Brexit, making it the largest single-day loss in history. Additionally, across spillover bands 3, 4, and 5, Figure 2 shows evidence of delayed contagious effects from the EDC of 2011/12 and the COVID-19 pandemic.

We attribute the marginal increase of spillover connections in 2013 and 2019/2020, respectively, to the 2011/12 EDC and the COVID-19 pandemic's unstable market circumstances. The debt market was disrupted as a result of COVID-19, and bond purchasers suffered losses that would be difficult to recover, as Gupta et al. [5] advocated. Pursuant to the findings, we deduce the delayed contagion theory proposed in the works of Boako and Alagidede [74], Ijasan et al. [75], Owusu Junior [57], and Owusu Junior et al. [58] based on the dramatic increases in spillovers across the bands that occurred in 2017, succeeding the Brexit effect [64–66]. Figure 2 shows that there are signs of contagion in the distinct spillover plots for Islamic and G6 bonds. It is important to notice that USA, Canada, and UK are the origins of the inferred contagion across all time horizons, since they are the biggest contributors/transmitters of shocks across all markets examined.

Overall, our findings indicate that spillovers predominate in high frequency/spillover bands 1 and 2 (3.14 ~ 0.79 and 0.79 ~ 0.20, respectively), which reflect the short term. The entire spillovers across and within the Islamic and G6 bond markets, in other words, could be attributed to the short term. In comparison, whereas Islamic bonds are more likely to be immune to the shocks presented to global financial markets during the COVID-19 pandemic in the intermediate-to-long-term horizon, G6 bonds are more vulnerable to shocks due to the presence of sporadic volatility clusters revealed across all spillover bands in the studied period. The extant literature such as Akhtar et al. [52], Hkiri et al. [54], Naeem et al. [56], and Roukiane and Marzouki [51], supports our results. Hkiri et al. [54], for example, found that although the contagion hypothesis remains true for both Islamic and conventional indices, Islamic indices dissociate from their conventional counterparts during turbulent periods. Akhtar et al. [52] also showed that Islamic assets have high capabilities to reduce volatility correlations of assets in a portfolio during financial

crises and this could be realised when at least one Islamic asset is contained in the portfolio.

5. Conclusions

The Baruník and Křehlík [49] (BK-18) spillover index was used in this research to look at the dynamic connectivity of spillovers between Islamic and conventional bond markets in order to illustrate the time- and frequency-domain dynamics of the two asset classes under various market circumstances. We use daily bond market indices for five major Islamic bond markets (India, Malaysia, Indonesia, Pakistan, and Qatar) and G6 economies (Canada, France, Italy, Japan, UK, and USA) from August 22, 2012, to September 17, 2021.

Through the BK-18 spillover index, we discovered that spillovers in the very short term (intraweek-to-fortnight) are relatively greater than those in the medium-to-long-term horizons, indicating that all bond markets examined react rapidly to shocks in the first few trading days. As a result, the Islamic and conventional bond markets examined are more sensitive to market shocks in the short term than in the long term, confirming Fama's [9, 10] EMH. We find that, in both Islamic and conventional (G6) bond markets, short-term spillovers are more important than intermediate-term spillovers. In the high-frequency band, USA, UK, and Canada (in order of spillover magnitude) are the most significant transmitters of shocks to the Islamic and G6 bond markets, particularly in the first spillover band (3.14 0.79, equivalent to 1 ~ 4 trading days). In the medium- and long-term timeframes, these nations are shown to be the biggest suppliers of shocks to the chosen Islamic and G6 stock markets, with the main distinction being that Canada's shock transmission surpasses that of UK. Among the markets examined, Pakistan is both the least contributor and least receiver of shocks. USA was discovered to be the biggest short-term receiver of spillovers, whereas UK absorbs the largest intermediate-to-long-term shocks.

Furthermore, volatility spillovers across Islamic bond markets are widespread (stable) only at high (low) frequencies throughout the COVID-19 timeframe. In G6 bond markets, on the other hand, spillovers are more visible and amplified throughout all spillover bands (short term, medium term, and long term). As a result, we find that, during market turbulences, conventional bond markets have more variable returns than Islamic bond markets across all time horizons. Based on our results, we propose that the nature of volatility spillovers between and within Islamic and/or G6 bond markets is time-varying and frequency-dependent, which is consistent with the HMH of Müller et al. [12], Lo's [11] AMH, and Owusu Junior et al.'s [14] CMH. The works of Akhtar et al. [52], Hkiri et al. [54], Naeem et al. [56], and Roukiane and Marzouki [51], among others, provide additional support for our findings. More importantly, in line with Forbes and Rigobon [71, 72], Ijasan et al. [75], Owusu Junior [57], Owusu Junior et al. [58], and Owusu Junior et al. [59], we infer contagion incidences (evidenced by substantial increases in spillovers), which are supplied by USA, Canada, and UK within the years 2013, 2016/17, and 2020/21. These are attributable to the EDC of 2011/12, the Brexit referendum [64–66], and the COVID-19 pandemic, respectively, and substantiate the delayed contagion hypotheses of Boako and Alagidede [74], Ijasan et al. [75], Owusu Junior [57], and Owusu Junior et al. [58].

Investors and governments will benefit greatly from our findings. Spillovers are time-varying and asymmetric, which should be noted by bond and equity investors. Specifically, amid financial and health crises, investors may utilise knowledge about market patterns and volatility to hedge their positions against lower asset returns, especially in the near term (up to about eight trading days), when spillover is more intense. According to the HMH and CMH, equity investors may change their investment strategy owing to heterogeneous occurrences and Islamic bonds may satisfy this objective. Notably, in the intermediate-to-long-term horizon, Islamic bonds provide diversification benefits relative to the G6 bonds. When forecasting bond yield volatility and constructing asset portfolios, portfolio managers should incorporate the information on policy amendments resulting from market shocks like the COVID-19 pandemic. During financial turmoil, policymakers should pay close attention to spillovers due to their capability of undermining cross-market connectedness. Portfolio and fund managers and policymakers could forecast the impact of their policies and reforms by using data on frequency dynamic spillover intensities and directions.

Data Availability

The bond yield indices for all the studied markets we extracted from EquityRT, which can be seen at https://equityrt.com/.

Conflicts of Interest

The author states that there are no competing interests of any kind.

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Research Article

Analyzing Performance of Banks in India: A Robust Regression Analysis Approach

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This research aims to analyze the impact of bank performance determinants on bank performance by applying robust regression analysis. For this, the relationship between return on assets and net interest margin with bank performance determinants has been discussed using robust regression. Robust regression offers a better and more realistic analysis owing to reducing the impact of outliers and influential data, and it is recommended for more precise results.

1. Introduction

Modern banking borrowing and lending activities help in the economic development of the country. Accepting deposits and lending activities expose the banks to various financial risks that are "credit risk, liquidity risk, market risk, and operational risk." The efficient management of these risks is an important factor behind bank profitability. The capital requirement of banks also depends on the management of these risks by the banks. As banks are highly leveraged financial institutions, the depositors' money must be kept safe by the bank in any adverse situation, and therefore, risk management becomes paramount for banking institutions. Any adverse situation faced by the banks can affect other sectors of the economy as well. Therefore, regulators greatly emphasize the effectiveness and stability of risk management in the banking system of an economy. Recent technological developments have also made the banking system even riskier. Therefore, there is a need for the adoption of the best risk management practices by banks that offer different products and services to different customers across the globe.

Commercial banks are significant for the Indian economy and are considered the heart of the financial system. The RBI is the main regulator of commercial banks in India. Commercial banks are classified as "public sector, private, and foreign banks." Recognizing the significance of commercial banks in economic development, 14 banks were nationalized in 1969, followed by another 6 in 1980. Later reforms in the highly regulated banking sector began in 1991 in India as a part of the overall structured reforms.

Financial deregulation and innovation in banking products and services have increased the importance of credit risk management. The Indian banking system has entered into a transition phase, and financial stability has become a need of the hour due to rising nonperforming assets. Credit risk management practices in banks affect the bank's performance. The objective of the study is thus to assess the impact of bank performance determinants on bank performance. The present study aims to understand the role of bank-specific regulatory norms (Basel norms), macroeconomic factors, and financial crises on the public-sector banks' performance operating in India using robust regression techniques.

2. Review of the Literature

This section deals with reviewing the literature on the measures of bank performance, its determinants, and how bank-specific and macroeconomic factors affect bank performance.

2.1. Bank Performance Measures. Profitability. Many studies [1–12] have used "return on assets" as a performance measure for commercial banks, while other studies [13–15, 4, 16–21] employed return on equity as a bank performance measure. Other studies [4, 10, 17, 19, 22–25] have used net interest margin as bank performance measure.

2.2. Bank-Specific Factors. Bank size, bank capital, operating efficiency, liquidity, credit risk, productivity, and income diversification are recognized as bank-specific determinants of bank performance in previous studies.

2.2.1. Bank Size. Existing studies show a positive as well as a negative relationship between bank performance and bank size. Studies that showed a positive relationship [26, 13, 10, 4, 17, 18, 7, 19, 20, 11] suggested that banks become more profitable when they grow in size. However, some studies showed that when banks increase their size, the additional operating costs of banks decrease their profits [15, 27, 28, 5, 12, 9, 25, 29].

2.2.2. Bank Capital. Bank capital indicates banks' ability to meet deposit demand and to protect customer savings during any financial turmoil. Many existing studies [30, 26, 15, 13, 3, 27, 31] observed a positive relationship between bank capital and bank performance with reference to profitability, indicating banks with adequate capital better exploit market opportunities and improve earnings.

2.2.3. Operating Cost. Many previous studies including Salike & Ao [30]; Kosmidou [26]; Kohlscheen et al. [15]; Sarpong Kumankoma [27]; Petria et al. [10], Rahman et al [4] Alexiou & Sofoklis [18]; Mirzaei & Mirzaei [29]; Naifer [32]; Curak et al. [33]; and Athanasoglou et al. [20] have shown a significant inverse relation of "bank profitability" with "operating costs," indicating a negative relationship of cost with performance. A high cost-to-income ratio indicates management inefficiency and low profitability.

2.2.4. Liquidity. Both poor liquidity and high liquidity may lead to poor performance of banks. The poor liquidity position of a bank can expose banks to bankruptcy, while high liquidity indicates inefficient performance. Previous studies have reported both negative and positive relationship of liquidity with bank profitability. Albulescu [16]; Salike and Ao [30]; and Kohlscheen el at. [15] found a positive relationship between bank liquidity and bank profitability, while Naifar [32] and Tan and Floros [23] reported an insignificant relationship. Kosmidou et al. [25]; Mirzaei and Mirzaei [29]; Al-Jafari and Alchami [11]; and Islam and Nishiyama [21] found a negative relation of liquidity with bank profitability [34].

2.2.5. Credit Risk. The expected relation between credit risk and bank profitability is negative. Many previous studies, like Salike and Ao [30]; Petria et al. [10], Majumder and Li [3]; Brahmaiah [8]; Petria et al. [10]; Samad [35]; Kosmidou [26]; Sufian & Chong [28]; Menicucci & Paolucci [17]; Mirzaei & Mirzaei [29]; Athanasoglou et al. [20]; and Al-Jafari & Alchami [11] reported the negative impact of credit risk on bank profitability. Studies such as Chen et al. [13]; Abdullah et al. [5]; Alhassan et al. [6]; Tan & Floros [23]; Sufian & Habibullah [19]; Kosmidou et al. [25] showed a positive association between the two variables.

2.2.6. Productivity. "Higher productivity results in high profitability for the banks. Hence a positive relationship is anticipated between productivity and bank profitability [36]. Many studies like [3] reported a positive impact of productivity on bank profitability, while other studies [5, 18] reported a negative relationship.

2.2.7. Income Diversification. It is expected to impact bank profitability positively. However, a mixed relationship was reported in the empirical evidence. Many studies like Salike & Ao [30]; Majumder and Li [3]; Sarpong Kumankoma et al. [27]; Sufian & Chong [28]; Sufian [37]; Sufian & Habibullah [19] identified a positive relationship between income diversification and bank profitability. Studies-like Islam & Nishiyama [21]; Sufian & Habibullah [19] indicated an insignificant relation while Rahman et al [4]; Reddy [24]; and Sufian & Habibullah [19] reported a negative relationship between the two variables.

2.3. Banking Regulations

2.3.1. Basel Norms. Basel Accords are the guidelines by the BCBS to ensure adequate bank capital to absorb unexpected losses. The Basel I Accord issued in 1988, focusing on credit risk only, prescribed a capital adequacy ratio (CAR) of 8% with different weights for different types of credit exposure to calculate the risk-weighted asset (RWA). The market risk was later included in the computation of the minimum CAR of the bank during the 1990s. Due to the limitations of Basel I accord, Basel II Accord was issued in 2004. The three pillars of Basel II accord are as follows: (1) minimum capital requirement for credit, operational, and market risks; (2) supervisory review process; and (3) market discipline [40]. The 2008 financial crisis showed the inadequacy of Basel II Accords, and a long-term stricter requirement of capital standards known as Basel III was introduced in 2010-11, which also required a pair of liquidity ratios to be maintained by the banks. Many previous studies, like Rahman et al. [4] & Roy [39], used Basel norms as a dummy variable for finding the impact of banking regulation on bank performance [40].

2.4. Macroeconomic Variables. This section highlights the existing studies on the macroeconomic determinants of bank profitability.

2.4.1. Growth in GDP. "A positive association is expected between bank profitability and the growth in GDP during a period when the economy is relatively stable and growing [41]. A relatively stable and growing economy creates a conducive atmosphere for investment and bank profitability. Many studies like Salike and Ao [30]; Majumder and Li [3]; Yüksel et al. [14]; Kosmidou [26]; Chen et al. [13]; Curak et al. [33]; Alhassan et al. [6]; Reddy [24]; and Kosmidou et al. [25] highlighted a positive relation of growth in GDP with bank profitability." However, some studies like Kohlscheen et al. [15]; Rahman et al. [4]; Alexiou & Sofoklis [18]; Mirzaei & Mirzaei [29] found an insignificant relationship between the two variables while studies like Tan & Floros [12]; Brahmaiah [8]; Bouzgarrou et al. [9]; Al-Jafari & Alchami [11]; Islam & Nishiyama [21] reported negative relationship.

2.4.2. Inflation Rate. Existing literature shows heterogeneous results in relationship between inflation rate and bank profitability. Many previous research like Yüksel et al. [14]; Chen et al. [13]; Rahman et al. [4]; Abdullah et al. [5]; Brahmaiah [8]; Bouzgarrou et al. [9]; Kosmidou et al. [25]; Athanasoglou [20]; Al-Jafari & Alchami [11]; Islam & Nishiyama [21]; Tan & Floros [23] reported positive relationship, Sufian & Habibullah [19]; Sufian [37]; Kohlscheen el at. [15]; Alexiou & Sofoklis [18] indicated an insignificant relationship in their study, while Sufian & Chong [28]; Alhassan et al. [6]; Mirzaei & Mirzaei [29]; Salike & Ao [30]; Kosmidou [26] indicated negative relationship. The operating costs of banks may increase due to inflation, but the inflationary condition may increase productive activity, which is positive for bank profitability [42].

2.5. Financial Events

2.5.1. Financial Crises. A few studies attempted to find the impact of the financial crisis of 2008 on the bank's profitability. Yüksel et al. [14] reported a negative impact of the financial crisis, while Bouzgarrou et al. [9] found a positive impact of it. Derbali [43] found that Islamic banks were not affected by the financial crisis of 2007.

3. Objectives of the Study

The study aims to achieve the following objectives:

(i) To find the bank's performance determinants

(ii) To analyze the impact of bank-specific variables on the financial performance of public-sector banks using robust regression analysis

(iii) To study the impact of banking regulations on the performance of public-sector banks using robust regression analysis

4. Research Hypotheses

The following hypotheses have been framed to analyze the Impact of Basel Norms on the financial performance of public-sector banks in India:

(i) Bank-specific variables have a significant impact on financial performance of public-sector banks in India

(ii) Banking regulations have significantly impacted the financial performance of public-sector banks in India

5. Research Methodology

The present study is both descriptive as well as analytical in nature. This study concentrates on analyzing the impact of bank performance determinants on the financial performance of public-sector banks operating in India by applying robust regression analysis.

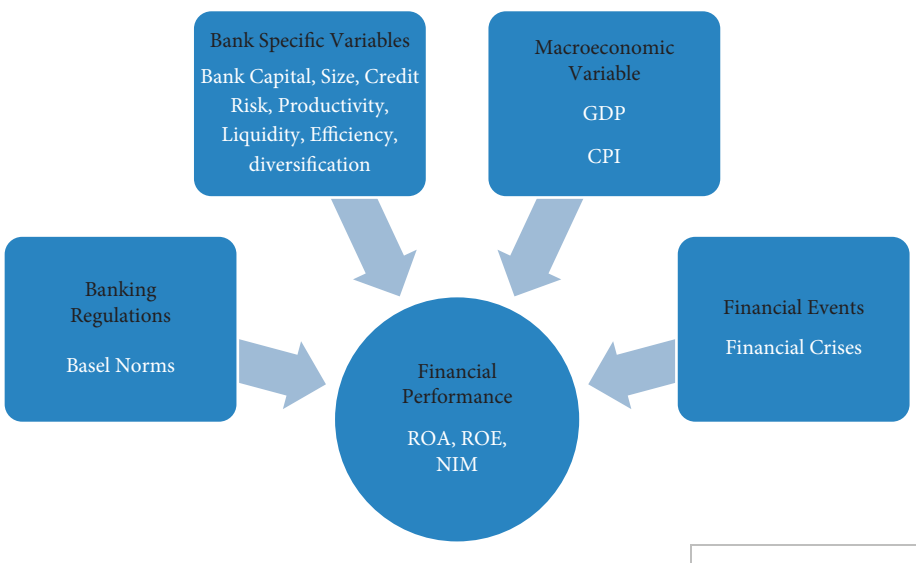
5.1. Data Source and Sample. The present study relies on secondary data on selected parameters of the public-sector banks operating in India. The RBI database has been used to extract data on selected parameters of the public sector for a period from 2005 to 2018. 21 banks were chosen as a sample of public-sector banks operating in India. All those government-owned banks that were operating in India during 2005–2018, and whose data were available for all the selected parameters, were selected for the present study.

5.2. Selected Variables for the Study. Table 1 highlights various financial parameters used in the study to analyze the impact of Basel norms on the financial performance of public-sector banks in India. These variables have been classified as "bank performance variables, bank-specific variables, macroeconomic variables, banking regulations, and financial events."

5.3. Framework of the Study. The framework of the study is shown as a flowchart, given by the authors.

Table 1: Description of variables of the study.

Parameters	Proxy measures	Acronym
Performance variables		
Profitability	Return on assets	ROA
	Net interest margin	NIM
Bank-specific variables		
Bank capital	Capital adequacy ratio	CAR
Credit risk	Net nonperforming assets to net advance	NNPANA
Liquidity	Liquid assets to total assets ratio	LATA
Bank size	Log of assets	LNA
Operating efficiency		OPEXTA
Productivity		PPE
Income diversification		NONIITI
Banking regulations		
Basel norms	Basel I era (dummy)	B1
	Basel II era (dummy)	B2
	Basel III era (dummy)	B3
Macroeconomic variables		
Economic growth	Gross domestic growth rate	GDP
Inflation	Consumer price index	CP
Financial events	Financial crises (dummy)	FC



5.4. Expected Relationship of Study Variables. The expected impact of the variables under study on financial performance of the bank has been summarised in Table 2.

5.5. Robust Regression Models. The study analysed the impact of bank-specific variables, banking regulations, financial crises, and macroeconomic variables on public-sector banks performance. For this purpose, the following models were developed based on previous literature:

(1) $\mathrm{ROA}_{it} = \beta_1 + \beta_2 \quad \mathrm{LNA}_{it} + \beta_3\mathrm{NNPANA}_{it} + \beta_4\mathrm{CAR}_{it} + \beta_5\mathrm{LATA}_{it} + \beta_6\mathrm{OPEXTA}_{it} + \beta_7\mathrm{PPE}_{it} + \beta_8\mathrm{NONIITI}_{it} + \beta_9\mathrm{GDP}_{it} + \beta_{10}\mathrm{CPI}_{it} + \beta_{11}\mathrm{B2}_{it} + \beta_{12}\mathrm{B3}_{kit} + e_{it}$

(2) $\mathrm{NIM}_{it} = \beta_1 + \beta_2\mathrm{LNA}_{it} + \beta_3 \quad \mathrm{NNPANA}_{it} + \beta_4\mathrm{CAR}_{it} + \beta_5\mathrm{LATA}_{it} + \beta_6\mathrm{OPEXTA}_{it} + \beta_7\mathrm{PPE}_{it} + \beta_8\mathrm{NONIITI}_{it} + \beta_9\mathrm{GDP}_{it} + \beta_{10}\mathrm{CPI}_{it} + \beta_{11}\mathrm{B2}_{it} + \beta_{12}\mathrm{B3}_{kit} + e_{it}$

In these equations, i shows cross-sectional dimension across the selected sample banks, t denotes the years, and ε is for the random error term. Pit denotes the financial performance of banks proxied by ROA and NIM. β_1 is the constant term. LNA is the bank size, NNPANA is for credit risk, and CAR is for capital adequacy. LATA is the liquidity, OPEXTA is management efficiency, PPE is productivity, and NONIITI is for income diversification. GDP is used for economic growth, while CPI is for inflation. B1, B2, and B3 are dummy variables used for Three Basel Eras.

6. Results of Empirical Analysis

6.1. Descriptive Analysis. Table 3 reports the descriptive analysis of variables under study. It is evident from Table 3 that mean values of NIM and ROA are 2.45% and 0.82%, respectively, while their maximum values are 3.78% and 2.46%, respectively, and their minimum values are 0.23%

Table 2: Expected relationship of study variables.

Variables	Bank performance
Capital adequacy ratio (CAR)	−/+
Basel norms (B1, B2, B3)	−/+
Bank size (LNA)	+
Credit risk (NNPANA)	—
Liquidity (LATA)	−/+
Productivity (PPE)	+
Cost inefficiency (OPEXTA)	—
Income diversification (NONIITI)	+
GDP growth rate (GDP)	−/+
Inflation (CPI)	−/+
Financial crises (FC)	—

Table 3: Descriptive statistics.

	NIM	ROA	PPE	CAR	NNPANA	GDP	CPI	LNA	LATA	NONIITI	OPEXTA
Mean	2.45	0.82	0.57	12.21	2.99	7.00	0.07	14.20	8.45	11.28	2.19
Median	2.43	0.76	0.48	12.17	1.72	7.54	0.06	14.29	7.93	10.99	1.54
Maximum	3.78	2.46	4.70	18.16	16.69	8.50	0.12	17.36	23.63	24.82	21.74
Minimum	0.23	0.07	0.04	8.69	0.15	3.09	0.02	10.53	2.80	2.07	0.56
Std. dev.	0.60	0.43	0.48	1.34	3.22	1.44	0.03	1.09	3.02	3.45	2.88
Observations	294	294	294	294	294	294	294	294	294	294	294

Source: authors' calculation.

Table 4: Correlation matrix for the dependent and independent variables.

	NIM	ROA	PPE	CAR	NNPANA	GDP	CPI	LNA	LATA	NONIITI	OPEXTA
NIM	1.00	0.28	−0.31	0.23	−0.39	0.05	0.01	0.28	−0.06	0.08	0.05
ROA	0.28	1.00	0.56	0.17	−0.03	−0.06	0.18	0.21	−0.13	0.34	−0.10
ROE	0.26	0.92	0.52	0.07	0.02	−0.05	0.18	0.18	−0.09	0.30	−0.08
PPE	−0.31	0.56	1.00	−0.13	0.49	−0.03	−0.02	−0.14	0.04	0.16	−0.07
CAR	0.23	0.17	−0.13	1.00	−0.49	−0.14	0.36	0.27	−0.10	0.21	0.03
NNPANA	−0.39	−0.03	0.49	−0.49	1.00	0.22	−0.58	−0.47	0.16	0.10	0.07
GDP	0.05	−0.06	−0.03	−0.14	0.22	1.00	−0.48	−0.07	0.06	0.11	0.02
CPI	0.01	0.18	−0.02	0.36	−0.58	−0.48	1.00	0.23	−0.23	−0.20	−0.02
LNA	0.28	0.21	−0.14	0.27	−0.47	−0.07	0.23	1.00	0.10	0.27	−0.51
LATA	−0.06	−0.13	0.04	−0.10	0.16	0.06	−0.23	0.10	1.00	−0.03	−0.10
NONIITI	0.08	0.34	0.16	0.21	0.10	0.11	−0.20	0.27	−0.03	1.00	0.12
OPEXTA	0.05	−0.10	−0.07	0.03	0.07	0.02	−0.02	−0.51	−0.10	0.12	1.00

Source: authors' calculations.

and 0.07%, respectively. The mean value of CAR during the study period (12.21%) has been higher than the required capital adequacy ratio of 10% in India. The mean value for NNPANA measures for credit risk for banks in the study is 2.99%. The maximum and minimum values for NNPANA are 16.69% and 0.15%. The average value of NIITI, a measure of business diversification, is 11.28%. Table 3 depicts that the average value of OPETA, a measure of inefficiency used in the study, is 2.19%. The table also shows the mean value of liquidity (LATA) as 8.45%. The maximum and minimum values of LATA vary from a maximum of 23.63% to 5.43%. Profit per employee (PPE), a measure for productivity, has an average value of 0.57 with a standard deviation of 0.48. GDP and CPI were used as macroeconomic variables in the study. The mean value of GDP is 7.0% during the study, while the average value of CPI was 0.07.

6.2. Correlation Analysis. Table 4 shows Pearson's correlation coefficients. If it is greater than 0.80, then there is an issue of multicollinearity. The table shows that dependent variables have no multicollinearity. It is shown in the table that CAR, GDP, CPI, LNA, NONIITI, and OPEXTA are positively associated while PPE, NNPANA, and LATA are negatively associated with NIM. In case of ROA, CAR, CPI, LNA, and NONIITI are positively associated, while NNPANA, GDP, LATA, and OPEXTA are inversely related to ROA. Furthermore, ROE has a positive association with PPE, CAR, NNPANA, CPI, LNA, and NONIITI while being negatively associated with GDP, LATA, and OPEXTA.

The correlation matrix depicts that "productivity, bank capital, bank size, and business diversification" has a positive impact on bank profitability while "credit risk, ownership structure, liquidity, nontraditional activity, and inefficiency" negatively impact bank profitability.

Table 5: Robust regression analysis with return on assets.

ROA as dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LNA	0.897 (−0.13)	0.152 (1.43)	0.45 (−0.74)	0.28 (−1.07)	0.220 (1.23)	0.492 (−0.69)	0.534 (−0.62)
NNPANA	0.000* (−6.62)	0.000* (−8.69)	0.0011* (−3.27)	0.024** (−2.24)	0.000* (−6.11)	0.000* (−5.30)	0.001* (−3.10)
CAR	0.0005* (3.50)	0.29(1.06)	0.07***(−1.81)	0.0004* (3.55)	0.136 (1.48)	0.221 (-1.22)	0.047** (1.98)
LATA	0.000* (−4.25)	0.0001* (−3.92)	0.056*** (−1.91)	0.0008* (−3.35)	0.0003* (−3.66)	0.007* (−2.67)	0.003* (−2.93)
OPEXTA	0.454 (−0.75)	0.37(0.89)	0.296 (−1.04)	0.08*** (−1.74)	0.479 (0.71)	0.29 (-1.05)	0.227 (−1.20)
PPE	0.000* (34.40)	0.000* (24.18)	0.000* (24.75)	0.000* (31.40)	0.000* (22.73)	0.000* (27.80)	0.000* (31.79)
NONIITI	0.000* (5.21)	0.000* (6.97)	0.000 (8.88)	0.000* (5.76)	0.000* (6.99)	0.000* (7.33)	0.0001* (3.92)
GDP				0.29 (−1.05)	0.565 (0.57)	0.467 (0.72)	0.496 (−0.68)
CPI				0.0001* (4.00)	0.044** (2.00)	0.000* (−4.71)	(0.34) (−0.95)
B1	0.000* (11.72)			0.000* (12.45)			0.008* (2.64)
B2		0.002* (−3.09)			0.002* (−3.06)		0.000* (−5.01)
B3			0.000* (−7.15)			0.000* (−9.03)	0.000* (−12.00)
Constant	0.355(−0.92)	0.356) (−0.92)	0.036** (2.09)	0.33(−0.95)	0.112(−1.58)	0.005* (2.77)	0.061*** (1.86)
Adjusted R^2	0.554	0.455	0506	0.570	0.457	0.527	0.575

Numbers in parentheses indicate z-statistics. ***,**,*Statistically significant at 10, 5, and 1 percent levels, respectively.

Table 6: Robust regression analysis with net interest margin.

NIM as dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LNA	0.883 (0.14)	0.690 (0.39)	0.747 (0.32)	0.404 (0.83)	0.435 (0.77)	0.022 (2.27)	0.075*** (1.77)
NNPANA	0.000* (−8.04)	0.000* (−8.79)	0.000* (−7.87)	0.000* (−8.71)	0.000* (−10.16)	0.000* (−4.17)	0.003* (−2.94)
CAR	0.0004* (3.54)	0.0002* (3.71)	0.0008* (3.38)	0.0003* (3.65)	0.020** (2.32)	0.066*** (1.83)	0.014** (2.43)
LATA	0.824 (0.22)	0.980 (−0.02)	0.910 (0.10)	0.621 (−0.49)	0.721 (−0.35)	0.249 (−1.15)	0.114 (−1.57)
OPEXTA	0.000* (136.10)	0.000* (139.16)	0.000* (139.36)	0.000* (134.19)	0.000* (136.81)	0.14(1.44)	0.549 (0.59)
PPE	0.000* (4.23)	0.000* (4.52)	0.000* (4.56)	0.000* (5.46)	0.000* (5.45)	0.390 (0.85)	0.590 (−0.53)
NONIITI	0.0016* (−3.14)	0.0006* (−3.42)	0.0009* (−3.33)	0.0003* (−3.62)	0.0006* (−3.41)	0.374 (−0.88)	0.134 (1.49)
GDP				0.996 (0.004)	0.69 (0.39)	0.48 (0.69)	0.260 (−1.12)
CPI				0.0006* (−3.43)	0.000* (−4.20)	0.000* (−8.77)	0.311 (−1.01)
B1	0.211(1.25)			0.687 (−0.40)			
FC							0.0000* (−5.38)
B2		0.118(−1.56)			0.017** (2.38)		0.029** (−2.17)
B3			0.49(0.68)			0.000* (−6.87)	0.0000* (−6.68)
Constant	0.214 (0.83)	−0.061 (0.95)	0.97 (−0.02)	0.580 (0.55)	0.178 (1.34)	0.0001* (3.84)	0.003* (2.92)
Adjusted R^2	0.437	0.439	0.437	0.448	0.456	0.394	0.433

Numbers in parentheses indicate z-statistics. ***,**,*Statistically significant at 10, 5, and 1 percent levels, respectively.

6.3. Robust Regression Analysis. A robust regression analysis was conducted to analyze the impact of bank performance determinants on the financial performance of public-sector banks in India. The results of robust regression analysis have been stated in Tables 5 and 6.

7. Results and Discussion

Table 5 gives the empirical findings of the seven models with ROA as a measure of bank performance. The robust regression analysis results depicts that Basel I norms had positively and significantly impacted ROA of public-sector banks, while Basel II and III had negatively and significantly affected public-sector banks' performance, implying that more stringent policies of Basel II and Basel III had adverse effects on public-sector bank performance.

Among the bank-specific variables, all the models (1–7) depict the same impact of bank size (LNA) and bank risk (NNPANA) on the bank performance (ROA). The findings show that bank size had no significance on the public-sector banks' performance across all the seven models, unlike earlier studies which showed a positive relationship [26, 13, 10, 4, 17, 18, 7, 19, 20, 11]. Bank risk had negatively and significantly impacted the bank's ROA during the study period, confirming that increasing nonperforming assets had negatively impacted the profitability of public-sector banks similar to many previous studies like Salike & Ao [30]; Petria et al. [10], Majumder and Li [3]; Brahmaiah [8]; Petria et al. [10]; Samad [35]; Kosmidou [26]; Sufian & Chong [28]; Menicucci & Paolucci [17]; Mirzaei & Mirzaei [29]; Athanasoglou et al. [20]; Al-Jafari & Alchami [11]. CAR shows positive and significant impact in three models (1, 4, and 7) like many existing studies, including Salike & Ao [30]; Kosmidou [26]; Kohlscheen et al. [15]; Chen et al. [13]; Majumder et al. [3]; Bansal et al. (2018), Sarpong Kumankoma [27]; Goddard et al. [31]. It is evident that CAR significantly and positively impact public-sector bank performance. Higher bank capital relates with higher bank profitability.

Cost inefficiency had not impacted ROA during the study period conforming the outcome of many previous Studies including Salike & Ao [30]; Kosmidou [26]; Kohlscheen et al. [15]; Sarpong Kumankoma [27]; Petria et al. [10], Rahman et al. [4] Alexiou & Sofoklis [18]; Mirzaei & Mirzaei [29]; Naifer [32]; Curak et al. [33]; and Athanasoglou et al. [20]. It was found that the measures of liquidity (LATA) across all the seven models had an inverse and significant relation with bank performance supporting the outcome of Kosmidou et al. [25]; Mirzaei and Mirzaei [29]; Al-Jafari and Alchami [11]; and Islam and Nishiyama [21] which indicates that banks earn more by lending more and maintaining lower liquid assets.

In all the seven models, Labour productivity (PPE) and income diversification (NONIITI) had a positive and significant relation with bank performance (ROA) similar results were found in Salike & Ao [30]; Majumder and Li [3]; Sarpong Kumankoma [27]; Sufian & Chong [28]; Sufian [37]; Sufian & Habibullah [19], implying that higher labour productivity and diversified income lead to higher profit for banks. Surprisingly, financial crises had a positive relation with the ROA of public-sector banks in India.

Among the macroeconomic variables, GDP growth rate had no significant impact on ROA of public-sector banks unlike Salike & Ao [30]; Majumder and Li [3]; Yüksel et al. [14]; Kosmidou [26]; Chen et al. [13]; Curak et al. [33]; Alhassan et al. [6]; Reddy [24]; Kosmidou et al. [25], which found positive impact. However, CPI affect the bank performance positively as indicated in the models 4 and 5 similar to Yüksel et al. [14]; Chen et al. [13]; Rahman et al. [4]; Abdullah et al. [5]; Brahmaiah [8]; Bouzgarrou et al. [9]; Kosmidou et al. [25]; Athanasoglou et al. [20]; Al-Jafari & Alchami [11]; Islam & Nishiyama [21]; Tan & Floros [23], while it shows negative impact in model 6 like Sufian & Chong [28]; Alhassan et al. [6]; Mirzaei & Mirzaei [29]; Salike & Ao [30]; Kosmidou [26] and no impact in model 7 like Sufian & Habibullah [19]; Sufian [37]; Kohlscheen et al. [15]; Alexiou & Sofoklis [18].

Table 6 empirically depicts the results of the seven models with NIM as a measure of bank performance. The robust regression analysis was employed and the empirical results of the study depict that Basel I norms had no significant impact on the NIM of public-sector banks, while Basel II and III negatively and significantly affected public-sector banks' performance, implying that the more stringent policies of Basel II and Basel III had adverse effects on public-sector bank performance.

Among the bank-specific variables, all the models (1–7) depict the same impact of bank size (LNA) and bank risk (NNPANA) on the bank performance (NIM), unlike [26, 13, 10, 4, 17, 18, 7, 19, 20, 11]. The findings show that bank size had no significance on the public-sector banks' performance across all the seven models. Bank Risk had negatively and significantly impacted NIM during the study period, supporting the outcomes of Salike & Ao [30]; Petria et al. [10], Majumder and Li [3]; Brahmaiah [8]; Samad [35]; Kosmidou [26]; Sufian & Chong [28]; Menicucci & Paolucci [17]; Mirzaei and Mirzaei [29]; Athanasoglou et al. [20]; Al-Jafari and Alchami [11] conforming that increasing nonperforming assets had negatively impacted Net Interest Margin of public-sector banks.

CAR shows a positive and significant impact in all models (except model 6) like Salike & Ao [30], Kosmidou [26]; Kohlscheen et al. [15]; Chen et al. [13]; Majumder and Li [3]; Bansal et al. (2018), Sarpong Kumankoma [27]; Goddard et al. [31]. It is evident that CAR on public sector positively impact bank performance. Higher bank capital relates with higher Net Interest Margin. Cost inefficiency had positively impacts Net Interest Margin during the study period. It was found that the measures of liquidity (LATA) across all the seven models had no significant relationship with NIM of public-sector banks unlike Albulescu [16]; Salike & Ao [30]; Kohlscheen et al. [15]; Kosmidou et al. [25]; Mirzaei & Mirzaei [29]; Al-Jafari & Alchami [11] and Islam & Nishiyama [21]. In the models (1–5), Labour productivity (PPE) had a positive and significant relationship with NIM of public-sector bank during study period like Majumder and Li [3] implying that higher labour productivity results in higher profit for banks. In the models (1–5), Income diversification (NONIITI) had a

negative and significant relationship with Net interest margin of public-sector banks like Rahman et el [4]; Reddy [24]; Sufian & Habibullah [19] implying that diversified income is related with lower NIM of banks. Financial crises had negatively impacted NIM of public-sector banks in India.

Among the macroeconomic variables, GDP growth rate had no significant impact on ROA of public-sector banks similar to Derbali & Lamouchi [44] but unlike Salike & Ao [30]; Majumder and Li [3]; Yüksel et al.[14]; Kosmidou [26]; Chen et al. [13]; Curak et al. [33]; Alhassan et al. [6]; Reddy [24]; Kosmidou et al. [25], while CPI affect the bank performance negatively as indicated in the models 4, 5, and 6 supporting results of Sufian & Chong [28]; Alhassan et al. [6]; Mirzaei & Mirzaei [29]; Salike & Ao [30]; Kosmidou [26] while it shows no impact in model 7 like Sufian & Habibullah [19]; Sufian [37]; Kohlscheen et al. [15]; Alexiou & Sofoklis [18]. It implies that during high inflation Net Interest Margin of Banks Reduces.

8. Conclusion

The robust regression analysis was employed to find the impact of bank performance determinants on the performance of the Indian banking sector. Empirical results depicts that Basel I norms had positively and significantly impacted ROA of public-sector banks while Basel II and III had negatively and significantly affected public-sector banks' performance, implying that more stringent policies of Basel II and Basel III had adverse effects on public-sector bank performance.

It can be concluded from the findings that bank size had no significance on the public-sector bank performance during the study period. Bank risk had negatively and significantly impacted bank performance of public-sector banks in India during the study period, confirming that increasing nonperforming assets had negatively impacted profitability of public-sector banks. CAR shows positive and significant impact in some models. Higher bank capital relates with higher bank profitability. Cost inefficiency had not impacted bank performance during the study period. It was found that the measures of liquidity (LATA) had an inverse and significant relationship with bank performance in most of the models, which indicates that banks earn more by lending more and maintaining lower liquid assets. However, cost inefficiency had positively impacted the net interest margin during the study period. It was found that the measures of liquidity (LATA) across all the seven models had no significant relationship with NIM. In almost all the models, labour productivity (PPE) and income diversification (NONIITI) had a positive and significant relationship with bank performance, implying that higher labour productivity and diversified income lead to higher profit for the banks. Income diversification (NONIITI) had a negative and significant relationship with the net interest margin of public-sector banks implying that diversified income is related to lower the NIM of banks. Surprisingly, financial crises had a positive relationship with bank performance in some models. Financial crises had negatively impacted NIM of public-sector banks in India.

8.1. Implications of the Study. Findings have implications for researchers, regulators, managers, and the government. Researchers can use robust regression analysis to analyze financial data. More vigilance is required by the RBI for high-risk portfolio banks, and the RBI should suggest higher provisioning requirements for such banks. [45] Banks should change their business model for complying with new banking regulations such as Basel III in a cost-efficient manner as considerable [46] cost may involve. Implementation of Basel III would require more capital. The government [47] is suggested to propose a plan for disinvestment in public-sector banks.

Data Availability

Data can be provided upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Research Article

Does Digital Finance Induce Improved Financing for Green Technological Innovation in China?

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Sustained and stable external financing, affected by the financial environment, is a necessary condition to support the green technological innovation of enterprises. This paper focuses on the impact of bettering the financial environment of digital finance on enterprise green technological innovation, as well as the mediating role of financing costs and financial flexibility in this process. Using China's data on manufacturing enterprises listed in Shanghai and Shenzhen from 2011 to 2018, the hypotheses are tested. The result suggests the following: (a) digital finance effectively promotes enterprises to carry out green technological innovation, specifically, the coverage and depth of digital finance can promote enterprises' green technological innovation, but the degree of digitization has no significant impact; (b) digital finance improves the financial environment by making up the shortage of traditional financial system through reducing financing problems such as "financing difficulty," "matching difficulty," and "supervision difficulty," which make effective contributions to enterprise green technological innovation; (c) financing costs negatively mediate the relationship between digital finance and enterprise green technological innovation, while financial flexibility positively mediates the relationship. Overall, our findings shed light on the role digital finance plays in shaping corporate environmental behavior—and ultimately innovation in sustainability—in financing constraint setting.

1. Introduction

Achieving an innovation-driven economy and embarking on the path of green development has become a widely recognized goal of people around the world. Green technological innovation can not only create economic value by relying on the innovation effect but also improve the environmental value by improving production and reducing energy consumption [1]. It helps build an efficient, clean, low-carbon, and circular green manufacturing system, which is a necessary way to achieve long-term green development. Meanwhile, green technological innovation is an activity of high risk and high investment, which needs the support of a large amount of external financing. However, due to the problems such as the existing technological spillover effect, long investment return period, difficulty to quantify the investment value, and so on resulting in information asymmetry, most enterprises carrying out green technological innovation are faced with financing difficulties [2]. In order to achieve long-term green development, the Chinese government began building a green financial system as early as more than ten years ago to help companies achieve green upgrades from the banking system, creditor market, and institutional investment. Although the measures have an active effect on energy consumption and pollutant emissions, there is no significant role in promoting corporate green technological innovation, and companies are still in the "innovative dilemma."

Technological innovation has an important impact on environmental quality, especially in developing economies [3]. Green technological innovation is one kind of technological innovation that is aimed at resource conservation and environmental protection [4]. For enterprises, developing green technology would be beneficial both to promote environmental performance through technological upgrading and process optimization and to promote long-

term financial performance by reducing environmental regulation costs. Therefore, a large proportion of literature studies have studied the internal and external factors that affect enterprises' green technological innovation.

According to Porter's Hypothesis, environmental regulation has a significant positive effect on corporate green technological innovation [5], which at the same has been confirmed by several studies [6–8]. However, the impact of environmental regulation on enterprises is realized through the external pressure, and it does not solve the unavoidable financial problems in enterprises' green technological innovation activities. According to the existing literature, convenient external financing is conductive to corporate R&D investment [9] and has a positive role in the process of technological innovation [10]. Yet, some literatures pointed out that financial obstacles caused by the inefficiency of the financial system can reduce the continuous R&D investment of enterprises and have a direct negative effect on the green technological innovation of manufacturing enterprises [2]. In the traditional financial system, commercial banks are the main source of external financial support for enterprises' innovation activities. Bank credit can provide green technological innovation funds for enterprises without deep pockets and improve their viability under current national environmental governance [11]. However, bank credit does not fully meet the external financing needs of corporate green technological innovation but also need to improve financial market tools to diversify R&D risks [12] and need the complementary role of corporate commercial credit [13], as well as government-subsidized funds to supplement [14], to reduce the insufficiency and instability of external financing and to maintain the continuous smooth of green technological innovation. Green financial policies are beneficial to improve the funding efficiency of the financial system to enterprise green technological innovation in China. Moreover, if financial institutions' investment in green technological innovation wants to be further improved, information disclosure needs to be resolved more effectively [15]. The existing literature studies show that the financing environment has an important impact on green technological innovation, while the financial system still has insufficient supply, low efficiency, and lagged information in financing support to enterprise green technological innovation. Therefore, how to enhance financial systems' positive effects of green technological innovation is worthy to be further studied.

As the same as technological innovation, financial innovation also has an important impact on environmental quality [16]. Digital finance is a vital financial innovation. Digital finance is booming with the progress of information technology, which makes use of technologies to transform service scenes and upgrade financing mode in various aspects. Block-chain technology reconstructs the trust mechanism of financing parties. Cloud computing technology promotes the connection between financial subjects. The development of digital finance is crucial to improving the efficiency of the financial system. First of all, digital finance combines finance with technology, which contributes to the accumulation of more leisure funds, increases the supply of financial resources for innovation activities, and promotes enterprise innovation through precise risk pricing and intensive business processes [17]. Second, digital finance helps to improve the financial structure, forces the transformation and upgrading of the financial sector, and enhances the efficiency of financial resource allocation and risk management ability [18]. At the same time, the traditional credit pricing model should be changed, the boundary constraints of traditional finance should be broken, the financing threshold and financing costs should be lowered, and the financing constraints of innovative enterprises should be alleviated [19]. Third, Fin-tech can help strengthen enterprise information transparency, correct resource mismatch in the financial system, provide financing parties with lower costs and better service experience, and help enterprises innovate by avoiding adverse selection and moral hazard problems in the financial market [20]. The development of digital finance will change the supply of financial elements and will also significantly affect the company's innovation activities.

Although the research studies mentioned above have provided some references for exploring the influence of digital finance on corporate green technology, there are still the following shortcomings. First of all, the existing literatures mostly pay attention to the impact of financial development on the environment from a macroperspective, but there is still a lack of research on the impact of financial development on the green behavior of microenterprises. Moreover, existing studies have focused on the improvement of digital finance to the financial system, but there is still a lack of attention to the specific effect of such improvement on the environment and the effect of such improvement on enterprises' green behavior. Based on this, this paper attempts to study financial development and environmental improvement from the perspective of enterprises. The novelty of this work is as follows: First, this paper builds a comprehensive analysis framework integrating digital finance, financial environment, and enterprises' green technological innovation and focuses on the impact of digital finance and its various dimensions on enterprises' green technological innovation, enriching the relevant theoretical research of financial environmental impact on green development of enterprises. Second, this paper focuses on judging whether the development of digital finance can make up for the problems of structural distortion, resource mismatch, and inefficiency in the traditional financial system in the actual economic activities and broadening the research boundary of the impact of digital finance development on the financial system. Thirdly, taking into account the two intervening variables of financing costs and financial flexibility, the paper tries to further explore the mechanism black box between digital finance and enterprises' green technological innovation.

2. Theory and Hypothesis

2.1. The Impact of Digital Finance on External Financial Environment. Promoting companies' commitment to green technological innovation is an important path to realize

green development and the inevitable choice for enterprises to achieve environmental value and financial value. However, green technological innovation is a systematic activity with a long investment period and high investment risk, which requires the support of a large amount of external financing [21]. There is no denying that China's traditional financial system is still immature, with a series of problems such as few financial suppliers, distorted capital allocation, and preference for short-term speculation [22]. It still needs to move forward in the direction of eliminating financial deficiency and further serving the real economy. Digital financial development, on the basis of financial operation pattern transformation and upgrading from the science and technological strength, helps to improve the breadth and depth of financial services, effectively compensate for insufficient financial systems, optimize financial resource allocation, improve corporate financing environments, and then provide more resource support for corporate green technological innovation. Accordingly, digital financial development can improve corporate green technological innovation financial environment in the following ways.

First, the development of digital finance broadens capital sources and financing channels and reduces the problem of "financing difficulty" of enterprises. In the traditional financial system, the supply sources of financial resources are mainly large commercial banks, securities institutions, fund companies, etc. Under this situation, a large number of "loose funds," namely, retail funds that have not been gathered and effectively used, are omitted in the market. Digital finance relies on big data, cloud computing, blockchain, Internet technology, artificial intelligence, and other scientific and technological means to collect and process massive data, build multiple service scenarios, gather the long-tail groups in the financial market, efficiently absorb and utilize a large number of "loose capital," and enrich the sources of capital. In addition, the financial means and service scenarios added by digital finance provide enterprises with more diversified financing channels and methods [23]. Therefore, the development of digital finance can significantly expand the company's financing options and provide sufficient financial support for enterprise green technology research and development.

Second, digital finance can effectively reduce information search costs and transaction costs and relieve the persistent disease of "matching difficulty" of financial resources. China's financial system, which is dominated by indirect financing, leads to a serious shortage of financial resource allocation efficiency. In view of the widespread information asymmetry problem, financial institutions are faced with high search costs and supervision costs, and enterprises also have a high cost of information self-verification [24]. The financial system favors large enterprises with deep financial resources and mature projects with low risks while growing enterprises with short development funds and long-term development projects with high risks are trapped in financing difficulties [25]. The development of digital finance makes it possible to collect massive enterprise data, standardize nonstandardized information data, and thereby perform depth analysis and excavation of it, which can significantly reduce the cost of search and transaction of financial institutions, and carry out a more comprehensive and accurate risk assessment on financing enterprises with lower cost and lower risk. In other words, the development of digital finance helps to avoid adverse selection in the financial market and reduce financing difficulties faced by green technological research and development.

Moreover, the development of digital finance strengthens the transparency of enterprise information and optimizes the dilemma of "supervision difficulty" of green technological innovation. The financing evaluation of traditional financial institutions focuses on the easily realizable assets of enterprises while neglecting the technological and innovation ability of enterprises, precisely because it is difficult to quantify the technology and innovation, the investment return period is long, and the development process is difficult to supervise [26]. The lack of information transparency makes it difficult for investors to trust enterprises, which also leads to the moral hazard problem of insufficient action of green technological development projects [27]. Digital financial technical support can accumulate credit data for enterprises and provide a credit basis for financing parties through comprehensive mining of enterprise information. At the same time, it can also improve the transparency and standardization of contract execution by signing smart contracts. Further, the credit system supported by big data and block-chain technological in digital finance can improve the internal and external information transparency of enterprises, supervise the behaviors of enterprises after the signing of contracts, shorten the time for enterprises to benefit from breach of contract, increase the cost of a breach of contract, and reduce the moral hazard behavior of "free rider" of enterprises. The establishment of such a continuous trust mechanism will help to change the attitude of financing parties in the long run, so that green technological innovation projects, which were originally unpopular, can get more financial support.

Based on the above analysis, hypotheses H1 and H2 are proposed in this paper.

Hypothesis H1: the development of digital finance has a significant positive impact on enterprise green technological innovation

Hypothesis H2a: the development of digital finance will lead to a stronger positive impact on green technological innovation of enterprises with poorer financing status by resolving the problem of "financing difficulty"

Hypothesis H2b: the development of digital finance will form a stronger positive impact on green technological innovation of enterprises with higher green innovation capacity by reducing the "matching difficulty" of financial resources

Hypothesis H2c: the development of digital finance will contribute to a stronger positive impact on green technological innovation of enterprises with weaker

information quality by reducing the "supervision difficulty" of green technological innovation

2.2. The Impact of Digital Finance on Internal Financial Environment. Adequate and stable internal capital is an important guarantee to smooth the R&D investment of enterprises [28] and keep the sustainable and long-term green technological innovation of enterprises. Digital finance can not only integrate resources and broaden financing channels to increase financing flexibility but also establish a trust mechanism to accelerate the completion of transactions and reduce transaction costs, which will benefit financing activities of enterprises from various aspects and help reduce financing costs of enterprises. The reduction of enterprise financing costs enables enterprises to have more funds available for deployment, which helps ensure the stable investment and continuous progress of green technological innovation activities of enterprises.

In addition, digital finance can help companies improve their financial resilience. Based on the decentralized technology of block-chain, digital finance records and stores the upstream and downstream enterprises' data from all links of the industrial chain, establishes the identity identification and tracking data platform, and activates the assets such as warehouse receipt, inventory, and receivables, which originally have a long realization cycle, so that the operating assets of enterprises can also be converted into cash flow at low cost and high efficiency. Moreover, digital technology converts traditional bank bills into digital bills, improves the recognition of interbank bills, improves the liquidity of commercial bills and other important financing instruments, and reduces their discount costs [29]. More importantly, the multiscene application and multilink connection of digital technology can also help enterprises improve their ability of information processing and make better decisions in managing cash flow and investment and financing activities. The circulation and management of more flexible and efficient operating assets will certainly be conducive to the improvement of the financial situation of enterprises, that is, the increase of the flexibility of the financial elasticity of enterprises. All these will provide support for the company's continued and stable green technological innovation activities by increasing and smoothing the funds available. Based on the above analysis, hypothesis H3 and hypothesis H4 are proposed in this paper.

Hypothesis H3: the development of digital finance promotes green technological innovation of enterprises by reducing the enterprises' financing costs.

Hypothesis H4: the development of digital finance promotes green technological innovation of enterprises by improving their financial flexibility.

The research framework of this paper is shown in Figure 1.

3. Experimental

3.1. Data and Samples. Considering that manufacturing enterprises are the most important subjects of green technological innovation, developing countries should pay more attention to the improvement of environmental quality [30, 31]. This paper takes Chinese manufacturing enterprises listed in Shanghai and Shenzhen as the research samples. The digital finance development data comes from the Digital Finance Inclusive Finance Index of Peking University, and the period of the digital finance index from 2011 to 2018 is taken as the time window of this paper. Green technological innovation data comes from the China Research Data Service Platform (CNRDS) and the State Intellectual Property Office's official website. Data at the microlevel were obtained from the China Stock Market and Accounting Research Database (CSMAR). In this paper, the digital financial index is matched with the data of listed companies, and the unbalanced panel data is constructed. The selected samples are further screened according to the following order: (1) delete the ST and *ST categories and delisted companies; (2) delete all listed companies with discontinuous or seriously missing important data; (3) delete asset-liability ratio greater than 1, namely, insolvent company; (4) delete companies that have fewer than three companies in an industry. After the above screening, a total of 7714 observed values were obtained. 1% tail reduction was adopted for all continuous variables in the data to eliminate the influence of extreme value.

3.2. Measurement of Variables. Green Technological Innovation (Greeninno). There exists a rich literature on green technological innovation from the industrial level to the enterprise level. Most researches use the energy consumption level in the production process, environmentally friendly research and development, and the green patent to measure green technological innovation. Considering the accuracy and data availability of variable measurement, this paper selects green patent applications of enterprise as the measuring variables [32, 33], and considering that the green invention patent technological content is higher, there is more representative substantial green technological innovation, so we choose the number of application for green patent for invention as indicators of green technological innovation. The specific measure is the number of invention patents add 1 and take the log, and the sum of the number of utility model patent applications is used as the robustness test.

Digital Finance (DFINA). Based on massive users' data, the Internet Finance Research Center of Peking University and Ant Financial jointly compiled the Digital Finance Inclusive Financial Index, which covers the data of 31 provinces and 337 cities in the Chinese mainland, including digital finance index. It also measures the development of digital finance in each region from three aspects of digital finance breadth, depth, and degree of digitization [34]. The index is most frequently used in the research of digital finance. In this paper, the digital financial inclusion index at the city level is used as the explanatory variable of this study, and the index is normalized.

Considering the large heterogeneity of green new technological research among enterprises, in order to

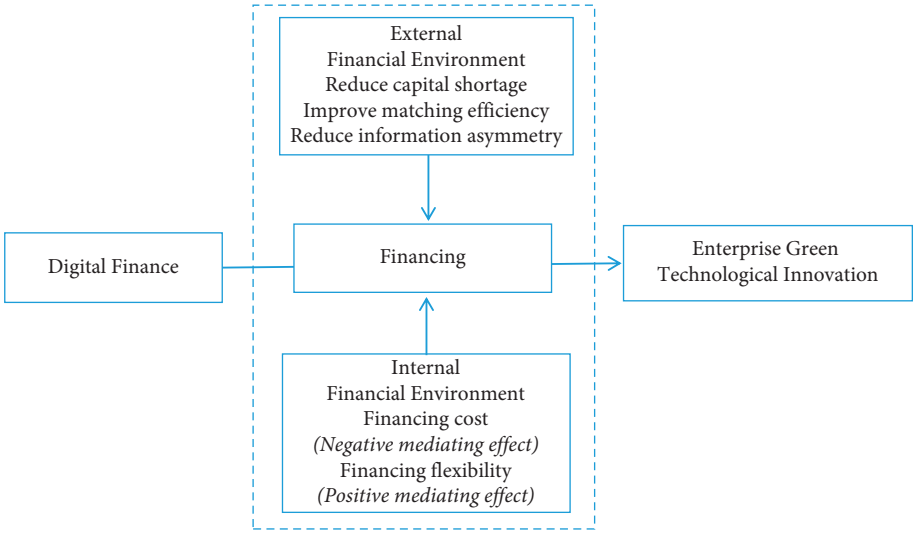

Figure 1: Research framework.

minimize the statistical impact caused by missing variables, this paper included enterprise variables as control variables from multiple aspects, specifically including (1) enterprise characteristics: enterprise age (age), enterprise size (size), and property rights (soe); (2) corporate governance: proportion of independent directors (outer) and degree of ownership concentration (no1); (3) financial situation: financial leverage (lever), current ratio (L-ratio); (4) corporate competitiveness: Lerner index (Lerner) and growth rate of operating income (growth).

3.3. Research Model. This paper focuses on the impact of digital finance on green technological innovation. In order to test the relationship between the two, we build an econometric model:

$$\text{Greeninno}_{i,t} = \alpha_1 + \beta_1 D\text{Fina}_{i,t-1} + \sum \gamma \text{Controls}_{i,t-1} + \sum \text{Ind} + \sum \text{Year} + \varepsilon. \quad (1)$$

In the regression equation, $\text{Greeninno}_{i,t}$ is the dependent variable green technological innovation, $D\text{Fina}_{i,t-1}$ represents the independent variable of the development degree of digital finance, and $\text{Controls}_{i,t-1}$ is all the control variables mentioned above. In order to overcome the endogenous problems that may be caused by the omission of variables and reverse causality, this paper, drawing on the research method of Wooldridge [35], treated the explanatory variables and all the control variables with a delay of one period. At the same time, based on the bidirectional fixed-effect model, we adopt the clustering robust standard error in the regression test by controlling the industry effect and time effect.

4. Results and Discussion

4.1. Descriptive Analysis. Table 1 reports the basic statistical results of the variables. The minimum value of the digital finance index is 0.1628 and the maximum value is 0.9619, indicating that the development level of digital finance is relatively unbalanced. The maximum value of green invention patent data is 4.9127, while the mean value is only 1.2628, and the median value is only 1.0986, indicating that the number of green patents in most manufacturing enterprises in China is relatively small, and the progress of green technological innovation activities is seriously insufficient. As can be seen from the results of financial leverage and liquidity ratio, there is a large gap in the financial situation of China's manufacturing enterprises, most of which have insufficient liquidity and are in a tight financial situation.

4.2. Basic Empirical Results Analysis. In Table 2, column one shows that the digital financial significantly positively affects the green technological innovation with statistically significant at the level of 1%, indicating that the development of digital financial level contributes to the improvement of the green technological innovation output of enterprises. With the development of digital finance, companies are facing a better financing environment, which makes enterprises have better green technological innovation performance. Therefore, H1 is supported.

Columns two to four in Table 2 report the impact of the digital financial segmentation dimension on green technological innovation. The coverage breadth and usage depth of the digital financial index have a positive effect on green technological innovation, which are statistically significant at the level of 1% and 5%, respectively. However, the digitization degree of inclusive finance has no statistically

Table 1: Descriptive statistical analysis of the main variables.

Variable	Variable definitions	Mean	Min.	Med.	Max.
DFINA	Digital finance index	0.6329	0.1628	0.6635	0.9619
Greeninno	Ln (number of invention patents +1)	1.2628	0.0000	1.0986	4.9127
Age	Ln (number of years since the establishment of the enterprise)	2.8477	2.0794	2.8904	3.5553
Size	Ln (Total assets)	12.9345	10.5801	12.7706	16.1704
Soe	Property right nature for state-owned enterprises take 1, otherwise take 0	0.3168	0.0000	0.0000	1.0000
Outer	Number of independent directors/number of boards	0.3765	0.0000	0.3571	0.8000
no1	The proportion of the largest shareholder of the company	0.3152	0.0300	0.2939	0.8824
Lever	Total liabilities/total assets	0.4044	0.0491	0.3997	0.8600
l-ratio	Current assets/current liabilities	2.6151	0.4409	1.7165	18.7324
Lerner	Lerner index of companies	0.0440	-0.2711	0.0251	0.4365
Growth	(Current operating income−previous operating income)/previous operating income	0.3735	-0.9069	0.2699	2.0421

Table 2: The basic regression results.

	(1) Greeninno	(2) Greeninno	(3) Greeninno	(4) Greeninno
L.Dfina	0.4740***			
	(3.187)			
L.Dfinabre		0.3584***		
		(2.643)		
L.Dfinadep			0.3327**	
			(2.092)	
L.Dfinadigtal				0.2543
				(1.241)
Control variables	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
_Cons	1.0398***	−3.0097***	−2.9914***	−2.9577***
	(6.154)	(−8.780)	(−8.740)	(−8.663)
N	4961	4960	4960	4960
r2_a	0.0390	0.1191	0.1186	0.1181

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

significant impact on the green technological innovation of enterprises. It shows that digital finance plays a positive role in promoting green technological innovation, and more attention should be paid to the extensive coverage of the development of digital finance in regions and the in-depth mining and application of various business scenarios, so as to promote the development of green technology of enterprises more effectively from these two dimensions.

4.3. Analysis of the Complementary Role of Digital Finance in Financing. As mentioned above, digital finance can make use of information technological advantages to effectively eliminate the "financing difficulty," "matching difficulty," and "supervision difficulty" caused by the inefficiency and high cost in the operation of the traditional financial system. Then, Does digital finance, integrated with the advantages of technology and model, make up for the lack of traditional finance in driving enterprise green technological research and development? In order to further explore the compensatory effect of digital finance on traditional finance and whether this effect can support green technological innovation, this paper examines the role of digital finance in the sample of different enterprises. In order to discuss whether to reduce "financing difficulty," samples of enterprises with different degrees of financing constraint and financial risk were investigated, respectively. In order to discuss whether to relieve "matching difficulty," samples of enterprises with different degrees of industry concentration and different enterprise life cycles were investigated, respectively. In order to discuss whether to optimize "supervision difficulty," the samples of enterprises with different quality levels of environmental disclosure reports and environmental governance reports were investigated.

4.4. Does It Reduce "Financing Difficulty"? According to the existing research, the higher the degree of financing constraints enterprises are faced with, the greater the financing dilemma; the higher the financial leverage of the same enterprise financial risk, the greater the burden, and the easier it is faced with financing difficulties, so this part chooses financing constraints and financial leverage as two indicators; according to the median of enterprise samples, they were divided into high financing constraint group and low financing constraints and the high and low financial risk groups. According to Hadlock and Pierce [36], the SA index is selected as the measurement index for financing constraints. The calculation formula is as follows: SA = = −0.737size + 0.043size2-0.04age. The calculation

formula of financial leverage is financial leverage = total liabilities/total assets.

Table 3 shows that the digital financial only has a significant positive impact on the green technological innovation of enterprises in the high financing constraint group and the high financial leverage group, and they remain significant at the 5% and 1% levels, respectively. The empirical results show that, in the case of financing constraints and financial dilemmas, the manufacturing enterprises with better development of urban digital finance can get more help to alleviate financing and financial difficulties and continue to develop green technological innovation activities. Digital finance has provided more capital sources and financing channels for green innovation projects, effectively alleviating the difficulties caused by capital problems to green innovation activities of enterprises, that is, helping enterprises with poorer financing status to reduce the "financing difficulty." Therefore, hypothesis 2a is supported.

4.5. Does It Reduce "Matching Difficulty"? Enterprises with a high concentration of market structure have a higher market position and are more likely to obtain more financial resources in the traditional financial system resource allocation. However, a lower concentration of market structure with more market competition is more conducive to green technological innovation. Enterprises in the low market concentration industry have greater green technological innovation motivation, while enterprises in competitive intensity industries face greater capital constraints for green technological innovation [37] and have a higher demand for financial resources. Therefore, this part chooses the HHI index to measure market concentration. Enterprises below the quantile of 25% are divided into the sample of enterprises with low industry concentration, and enterprises above the quantile of 75% are divided into the sample of enterprises with high industry concentration, so as to investigate whether digital finance helps enterprises in industries with low concentration which are not helped enough by the traditional financial system.

The enterprise life cycle is also closely related to green technological innovation capacity. It is different from the green innovation willingness and access to financial resources of enterprises in different stages of development. Enterprises in the growth stage and mature stage are the main forces to carry out technological innovation [38]. Enterprises in the mature stage have more abundant self-owned funds and external sources of funds, while enterprises in the growth stage often face greater capital pressure due to insufficient market recognition. Financial resources are needed not only to help the right business but also to help it at the right time. Therefore, this part examines whether digital finance has supported green technological innovation at the right time by dividing enterprises into three types: growth, maturity, and decline. Drawing on the cash flow model method of Dickinson [39], we use the positive and negative combination of the net cash flows of three kinds of activities, namely, business activities, investment activities, and financing activities, to reflect the characteristics of operating risk, profitability, and growth rate in different life cycles and divide enterprises into a growth period, maturity period, and decline period according to the different characteristics. This classification method can not only avoid subjective assumptions about the distribution of life cycle samples but also avoid the interference of inherent industry differences.

The results in Table 4 show that, according to the level of competition in the industry, digital finance only has a significant positive effect on the enterprises green technological innovation in industries with low concentration degree at the level of 5%. The development of digital finance is indeed more beneficial to green technological innovation for competitive enterprises that are not valued by the traditional financial system. According to the corporate life cycle, digital finance only produces positive promotion of green technological innovation activities for growth enterprises at the level of 1%. The above results show that digital finance has a stronger support for green technological innovation of enterprises, where more financial resources are required to carry out green technological innovation, but it is more difficult to obtain guarantees under traditional financial systems. That is to say, the development of digital finance has a stronger positive impact on green technological innovation of enterprises with a strong higher impact by relieving the stubborn problem of "matching difficulty" of financial resources. Therefore, hypothesis 2b is supported.

4.6. Does It Reduce "Supervision Difficulty"? The quality of a company's disclosure report can reflect its information transparency to a certain extent. The higher the information transparency, the more conducive it is to reduce information asymmetry [40] so that it is easier to obtain resources from the traditional financial system. In this part, enterprises are grouped according to the quality of environmental disclosure reports and environmental governance reports of listed companies, and the impact of digital finance on green technological innovation in enterprises with different information transparency is investigated, respectively.

The results in Table 5 show that, only for the sample of enterprises with low quality in environmental disclosure reports and environmental governance reports, the development of digital finance has a positive impact on green technological innovation, which is, respectively, significant at 1% and 10% levels. The results show that the development of digital finance is helpful to expand the supervision path of enterprise green technological innovation and increase corporate information transparency with insufficient performance in conventional information disclosure. Thus, more financial resources are obtained to support green technological innovation. Overall, digital finance has a stronger positive impact on green technological innovation of enterprises with weaker information quality by resolving the problem of "supervision difficulty." Hypothesis 2c is supported.

4.7. Mediation Effect Test. The above research verifies that digital finance development can significantly positively affect the innovation of corporate green technology by resolving

Table 3: Regression results of financing heterogeneity.

	Financing constraints		Financial leverage	
	(1) High financing constraint	(2) Low financing constraints	(3) High financial leverage	(4) Low financial leverage
	Greeninno	Greeninno	Greeninno	Greeninno
L.Dfina	0.4495**	0.2820	0.8576***	-0.1621
	(2.527)	(1.170)	(4.822)	(-0.709)
Control variables	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
_Cons	−2.7317***	−3.6914***	−4.2192***	−0.3192
	(−5.933)	(−6.805)	(−9.925)	(−0.504)
N	2791	2169	2705	2255
r2_a	0.13281	0.1797	0.1963	0.0649

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Regression results of enterprise characteristics heterogeneity.

	Industry concentration		Enterprise life cycle		
	(1)	(2)	(3)	(4)	(5)
	High concentration Greeninno	Low concentration Greeninno	Growth period Greeninno	Maturity period Greeninno	Decline period Greeninno
L.Dfina	0.0240	0.6299**	0.6177***	0.1499	0.3642
	(1.076)	(2.669)	(3.143)	(0.570)	(0.941)
Control variables	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes	Yes
_Cons	−3.3781***	−2.6101***	−3.0994***	−3.5479***	−2.8016***
	(−7.803)	(−5.590)	(−6.295)	(−5.985)	(−2.748)
N	1131	1367	2303	1771	739
r2_a	0.2119	0.1021	0.1294	0.1490	0.0712

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 5: Regression results of information quality heterogeneity.

	Environmental disclosure report		Environmental governance report	
	(1) High quality	(2) Low quality	(3) High quality	(4) Low quality
	Greeninno	Greeninno	Greeninno	Greeninno
L.Dfina	0.3135	0.5038***	0.4041	0.3528*
	(1.181)	(2.919)	(1.602)	(1.940)
Control variables	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
_Cons	−5.1182***	−1.7592***	−3.5259***	−3.1869***
	(−8.610)	(−3.706)	(−5.396)	(−7.211)
N	1570	3229	1537	3262
r2_a	0.2314	0.0741	0.1616	0.1135

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

problems with low traditional financial efficiency, and green technological innovation activities need to be supported by external financing and internal financing. However, can digital finance change the enterprise's internal environment to support innovation of enterprise green technology? What is the support mechanism in the process? It is necessary to further explore these problems. Based on the previous analysis, we select "financing costs (FC)" and "financial flexibility (FF)" as two effects and build a mediation effect model, such as type (2) - (4), the test number financial intermediary effect on the impact process digital finance on green technological innovation.

$$\begin{aligned}\text{Greeninno}_{it} &= \alpha_0 + \alpha_1 \text{Dfina}_{it-1} + \alpha_2 C_{it-1} + \sum \text{Ind} + \sum \text{Year} + \omega,\\ \text{mediator}_{it} &= \beta_0 + \beta_1 \text{Dfina}_{it-1} + \beta_2 C_{it-1} + \sum \text{Ind} + \sum \text{Year} + \sigma,\\ \text{Greeninno}_{it} &= \gamma_0 + \gamma_1 \text{Dfina}_{it-1} + \gamma_2 \text{mediator}_{it} + \gamma_3 C_{it-1} + \sum \text{Ind} + \sum \text{Year} + \tau.\end{aligned} \tag{2}$$

According to existing literature, there are various financial indicators that can reflect the financial flexibility of an enterprise. Among them, working capital can help to smooth the R&D investment of enterprises [41], so it is more suitable for deconstructing the impact mechanism of digital finance to green technological innovation. This part chooses standardized working capital as financial flexibility measure; the calculation formula is working capital divided by total assets. The financing costs are calculated by the formula of financial expenses divided by total liabilities.

The results in Table 6 show that digital finance significantly reduces the financing costs of enterprises, and the financing costs have a mediation effect between green technological innovation and digital finance, and both of them are significant at the 1% level. At the same time, digital finance is positively associated with financial flexibility and also plays a significant mediation effect on the promotion of green technological innovation by digital finance, and its significance remains above 5%. The results show that digital finance can significantly promote corporate green technological progress by reducing corporate financing costs and improving financial flexibility. Thus, hypotheses 3 and hypothesis 4 are supported.

4.8. Robustness Test. In this paper, three methods are used to conduct robustness tests. First, replace the empirical model. Considering the dependent variable green patent for numerical shows continuous integrity distribution and the characteristics of the zero value accumulation, using Tobit model; at the same time, control "time multiplied by industry" method of high-order joint fixed effects on empirical model robustness check; inspection results are shown in model (1) in Table 7; the relationship between coefficients changes slightly, but still keep at least 5% level of significance. Second, change the sample selection. The samples of enterprises that have never been applied for green patents are eliminated, and only the samples of enterprises that have been in stages of green technological innovation are considered. As shown in model (2), the test results show no substantial changes. Third, replace key variables. The number of green invention patent applications, the measurement index of the dependent variable, was replaced by the total number of green invention patent applications (GreenInnoAll). As shown in model (3), the test results did not change substantially. The robustness tests show that the empirical results of this paper are robust.

5. Discussion and Implications

5.1. Conclusions and Discussion. Green technological innovation carried out by enterprises, which plays an important role in improving environmental quality, is an activity that requires a large amount of financial support. Digital finance is crucial to the support. This paper sought to investigate the impact of digital finance on green technological innovation. The research sample was obtained from listed manufacturing companies of China from 2011 to 2018. The hypotheses set are tested by a two-way fixed effect model; combined with sample comparison analysis and mediation effect analysis, the following conclusions are drawn.

First, digital financial development can significantly promote enterprises' green technological innovation in various aspects. From the three dimensions of digital finance, both the coverage and use depth of digital finance development positively affect green technological innovation, while the influence of digitization degree is not significant. This shows one vital path to reveal that digital financing function is building digital financial networks that include more financial institutions and enterprises and then promoting the in-depth nesting between various financing businesses and digital financial networks. To be specific, more financial institutions and enterprises should first use digital finance, that is, join the digital financial network. On the basis of it, the possible business interactions between financial institutions and enterprises and between enterprises should be deeply explored. In this path, digital finance is useful to reduce financial costs and improve financial efficiency and then be the financial support of enterprises. This result is similar to Demertzis (2018) and added more details of the function of digital finance.

Second, the development strength of digital finance makes up for the problems of "financing difficulty," "matching difficulty," and "supervision difficulty" faced by enterprises in external financing. For many enterprises that need green technological upgrading, there are gaps between green R&D and external financing support in traditional financing systems. These gaps caused by numerous reasons, essentially information asymmetry, can be to some extent bridged by digital finance. This result supplies more pieces of evidence to the effects of digital finance on enterprises with different characteristics.

Third, the development of digital finance can improve the internal financing of enterprises' green technology innovation by reducing financing costs, improving financial flexibility. This helps enterprises to effectively carry out green technological innovation activities. This conclusion further verifies the improvement of digital finance on the financing environment of enterprises and helps to increase the understanding of the impact of digital finance development on the internal financial situation of enterprises.

5.2. Public Policy Implications. Some policy implications are provided. First of all, policies that support the development

Table 6: The mediation effect test.

	Financing costs			Financial flexibility		
	(1) Greeninno	(2) FC	(3) Greeninno	(4) Greeninno	(5) FF	(6) Greeninno
L.Dfina	0.3555**	−0.0041***	0.3154**	0.3555**	0.0536**	0.3336**
	(2.425)	(−3.602)	(2.146)	(2.425)	(2.206)	(2.269)
FC			-9.8262***			
			(-4.401)			
FF						0.4069***
						(4.244)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes	Yes	Yes
_Cons	−2.9955***	0.0109***	−2.8881***	−2.9955***	0.5245***	−3.2082***
	(−8.753)	(5.355)	(−8.481)	(−8.753)	(9.808)	(−9.214)
N	4960	4960	4960	4960	4956	4956
r2_a	0.1189	0.5360	0.1220	0.1189	0.5777	0.1217

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 7: Robustness test.

	(1) Greeninno	(2) Greeninno	(3) GreeninnoAll
L.Dfina	0.4505**	0.3978***	0.2866*
	(2.322)	(2.592)	(1.856)
Control variables	Yes	Yes	Yes
Time × industry	Yes		
Time effect		Yes	Yes
Industry effect		Yes	Yes
_Cons	−3.3920***	−3.0312***	−2.3086***
	(−6.256)	(−8.496)	(−6.547)
var(e.Greeninno)	2.1222***		
	(39.576)		
N	4960	4522	4960
r2_a		0.1051	0.1387

t statistics in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

of digital finance are necessary. The government should encourage financial institutions to develop digital finance-related businesses and apply them to more business scenarios to help build a broad digital financial network. On the premise of preventing financial risks, digital financial development policies should be given opportunities to try and make mistakes. More importantly, the government should help promote the construction of digital infrastructure at the national level and cultivate professionals who know both digitization and finance, to create favorable conditions for the development of digital finance. Secondly, the advantages of digital finance should be taken into account when formulating green finance policies. The government should encourage enterprises to make full use of the services provided by digital finance, as well as join the digital finance network, in order to promote green technological innovation. In this way, the advantages of efficient collection and processing of information in digital finance contribute to improving information quality of enterprises' green technological innovation, which not only give high-quality projects more financing but also give the process of green technology innovation more supervision to ensure the quality. Thirdly, the government should guide enterprises to make full use of digital financial services, adjust financing structure, reduce financing costs, and increase financial flexibility, in order to avoid tight cash flow jeopardizing enterprises' green technology innovation.

This paper has attempted to robustly test these hypotheses, but there remain some limitations and suggestions for future research. First, this paper tests and confirms that digital finance positively affects green technological innovation, but it does not further explore the sustainability of this impact, which is worthy of research. Second, mediation effect analysis only discusses the influence of internal factors of the enterprise, and the mediation effect of external factors of the enterprise needs further discussion.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Research Article

Does Indian Commodity Futures Markets Exhibit Price Discovery? An Empirical Analysis

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Price discovery function analyses the dynamics of futures and spot price behavior in an asset's intertemporal dimensions. The present study examines the price discovery function of the bullion, metal, and energy commodity futures and spot prices through the Granger causality and Johansen–Juselius cointegration tests. The Granger causality test results show bidirectional causality between the spot and futures returns for gold, silver, aluminum, lead, nickel, and zinc. The Johansen cointegration test shows that spot and futures prices are in the long-run equilibrium path for silver, aluminum, lead, nickel, zinc, crude oil, and natural gas. The vector error correction model results suggest that both the spot and futures markets are equally efficient in price discovery for the nickel. The spot market leads the futures market in price discovery for copper and zinc. However, the futures market leads the spot market in price discovery for silver, aluminum, and lead. The findings of the study suggest the market participants for implementing hedging and arbitrage strategies. It also helps the market regulators to examine the stability of these rapidly growing commodity futures markets in India.

1. Introduction

Commodities such as agriculture, metal, and energy are valuable to producers, processors, consumers, lenders, and brokers. Commodities trade on both spot and derivative markets across world commodity derivative markets [1]. Commodity derivative markets include trading of forwards and futures contracts, which derive its values from the market's spot commodities. As a welfare raising mechanism, an efficient commodity futures market plays a vital role in managing price risk uncertainty contextual to the primary commodities [2]. In an open economy, commodity futures markets hold pervasive importance in discovering a reference price for the producers and trade functionaries by reducing price volatility in the commodity prices and uncertain production decisions [3, 4]. Apart from price discovery, Li and Xiong [5] argued that the futures market is a significant instrument for risk management since it provides financial gains such as dissemination of information, and efficient resource allocation. Eventually, the spot price is affected by fundamental factors such as demand and supply, market structure, and government policies. In contrast, the futures price is driven by hedgers, speculators, traders, and other market participants. The study of price behavior in commodity futures markets provides a better analytical perspective towards futures contracts' pricing and on how futures market prices affect the commodities' spot price over time.

Interest in the Indian commodity futures markets is showing an increasing trend over the years. Commodity futures emerges as an attractive investment alternative to the security markets and is also recognized as an increasingly

popular vehicle to hedge investments [6]. The existing literature on price discovery and market efficiency in Indian commodity futures markets supports an efficient functioning commodity futures market's economic significance [7–9]. In developed countries, earlier studies emphasized the economic role and function of the commodity futures markets. The researchers' issues drawn considerable attention from the researchers that include intertemporal price behavior, hedging effectiveness, and basis relationship [10, 11].

However, in developing countries, futures markets are subject to higher government control, and reforms are relatively new. There is a gradual shift from an intervention approach to a market-based system in government policies. So, the commodity futures markets' economic role attracted the debate on these markets' economic benefits, such as price discovery and hedging [12]. Given the dynamic, economic, and institutional factors pertinent to the emerging economy, it is evident to expect a significant difference in the dynamics of commodity price behavior in these markets compared to that in a developed economy.

In the context of India, following the reform in the commodity derivative market since 2003, the commodity futures trading for agriculture, metal, and bullion commodities is growing significantly across major commodity exchanges [7, 13, 14]. However, the commodity futures market development's role in minimizing price risk uncertainty and economic efficiency in the spot markets needs to be studied. It is essential to explore the issues that explain the dynamics of Indian commodity futures markets' pricing behavior.

As the futures markets play a significant role in managing price risk and serves the price discovery role for the spot market in the economy, there is a need to look at the dynamics of the futures market's price behavior. In this context, a question arises about how does the futures prices behave?, how to interpret the information it conveys to the market?, and whether futures contracts are effective in reducing price risk? These issues are more pertinent for assessing the performance of the commodity futures market in India. The present study thus attempts to determine the price discovery role of the commodities traded in newly established futures exchanges. Prior studies for India were focused on spot and futures agricultural commodity markets [15–20], gold exchange traded funds [21], metals [22], spot and futures index [23, 24], daily futures, and spot closing prices for various commodities [25–27], both commodities and indices [28]. As compared with earlier literature, the novelty of the current study consists in the fact that three commodity groups are covered, namely, bullion (gold, and silver), metal (aluminum, copper, lead, and zinc), and energy (crude oil and natural gas) over a longer period, respectively, (2006–2018).

The remainder of this paper is organized as follows. Section 2 provides an overview of Indian commodity derivative markets. Section 3 presents the review of earlier literature. Section 4 is focused on empirical techniques. Section 5 exhibits the econometric outcomes. The last section concludes the manuscript and provides policy implications.

2. An Overview of Commodity Derivative Markets in India

The Government of India (GoI) brought various regulations to increase the markets' financialization for multiple commodities. The primary reasons include shifting the price fluctuation risk through hedging and performing the price discovery function and price reference for the spot market [29, 30]. Futures markets serve risk transference and price discovery functions to the economy [31–35]. The presence of speculators facilitates a risk transference function by buying a futures contract from hedgers. The price discovery function implies the use of futures prices on the price formation and transactions in the spot market [31, 33, 36]. So, both price discovery and risk transfer are crucial to justify the futures markets' economic benefit. However, the above features of a futures market are only theoretical. It is necessary to empirically validate these economic functions for evaluating the market performance to meet the objective of an efficient market structure for the commodity market. Alternatively, if futures markets are indeed performing the economic role as mentioned earlier satisfactorily, then there is a strong case for introducing new futures markets for other commodities.

Since the year 1875, commodity futures trading came into existence in India. Still, the market was said to be in hibernation for five decades resulting from strict government control (Kabra, 2007). In the year 2003–04, massive developments took place in the commodity futures market. On April 1, 2003, the government's notification led to the withdrawal of the previous announcements, which restricted futures trading of large quantities in India. Furthermore, a notification came in May 2003, canceling restrictions on nontransferable specific delivery forward contracts. Thus, GoI reduced the restriction in the futures market in expectation of a healthy market institution and efficient market structure. GoI further granted recognition to National Multi-Commodity Exchange of India Limited (NMCEIL), Ahmedabad, in 2002, Multi Commodity Exchange (MCX), Mumbai, and National Commodity and Derivatives Exchange Limited (NCDEX), Mumbai, in the year 2003, followed by Indian Commodity Exchange Limited (ICEXL), Gurgaon, in 2009. The establishment of national-level commodity exchanges resulted in a manifold increase in futures trading. The total turnover of futures trading increased from Rs. 1,294 billion to Rs. 60,070 billion from the year 2003–04 to 2017–18, whereas the total turnover to a gross domestic product increased from 4.6% in 2003–04 to 142.15% in 2017–18 [37, 38]. The developments in commodity futures markets resulted in the exponential growth of the commodity futures segment in the Indian economy. In recent years, commodity futures markets drew attention from the researchers regarding issues such as market efficiency, price discovery, risk management, international linkage, and other matters related to Indian commodity derivative markets [7–9, 14, 39–46].

3. Prior Literature on the Relationship between Futures and Spot Prices

The previous studies [31, 36, 47] emphasized the role of futures markets in price discovery in spot markets. Price discovery also predicts the expected futures spot prices and using the futures prices as a reference price in the spot market. It also helps in finding a reference price for the spot market and helps in identifying the feedback process of information of futures price and spot price. Futures prices shows the expected spot prices [48]. The futures market performs a price discovery function that depends upon the intertemporal relationship between spot and futures prices. Price discovery process reveals us whether futures (spot) market will lead to spot (future) market if all the available information passes on to futures (spot) price and then in spot (future) prices. When all available information is fully and instantaneously utilized in an efficient market to determine the market price, then futures price moves closely with its corresponding price in the spot market with no lag or lead in price movement from one market to another. If there is no difference in each of these markets, then both spot and futures market will react instantly without any lead or lag to the flow of information. Since futures and spot markets represent the same commodity, their prices should exhibit a similar reaction to a given information or event, a process facilitated by arbitrage [49]. A review of previous literature regarding price discovery in commodity futures markets is revealed in Table 1.

A lead-lag relation may exist between the spot and futures markets if one market processes information faster than the other. The factors which affect the lead-lag relationship include ease of short sale, lower transaction cost, institutional arrangement, and market microstructure effect. The lead-lag characteristics of futures and spot markets illustrate how rapidly one market incorporates information relative to others [57]. These characteristics also indicate the efficiency of their functioning and the degree of integration between the two markets [58]. Traders act faster at a lower cost in the futures market than spot market resulting in a lead-lag relation between futures and spot prices [59]. Lin, Chou, and Wang [60] argued that the time-differing lead-lag connection between futures and spot markets is caused, at least to some extent, by the impact of changeable investor confidence. Corredor, Ferrer, and Santamaria [61] revealed that throughout periods of high investor sentiment, the connection between the spot and futures markets diminishes substantially.

Futures trading facilitates the allocation of production and consumption over time by providing market guidance in holding inventories [48]. If the futures price for distant delivery is higher than that for early delivery, the postponement of consumption becomes attractive. Thus, a change in futures price results in a subsequent change in spot prices. Speculators prefer to hold a futures contract because they are not interested in the physical commodity per se, and a futures position can be offset easily. Furthermore, hedgers interested in the physical commodity and have storage constraints may hedge themselves by buying a futures contract. Therefore, both hedgers and speculators may react to information by transacting in futures rather than in the spot market. Consequently, futures price tends to lead the spot price. Chen, Wei, Jin, and Liu [62] found that in the energy futures markets, speculative attitude causes greater market movements than hedging sentiment. In light of the above, the issue of the causal linkage between two markets provides a clear motivation for studying the lead-lag relationship between futures and spot prices.

4. Data and Methodology

The present study used the spot and futures price data from the Bloomberg database. Twenty-one commodity exchanges are operating in India, among them, four exchanges, namely, MCX, NCDEX, NMCEIL, and ICEXL, are national-level commodity exchanges. The rest 17 are regional exchanges in various states to cater to local needs commodity price risk management. According to Futures Industry Association Report [63], MCX is ranked 22nd globally (ranked first among commodity exchanges of India) in terms of total contracts traded in bullion, currency, metal, and energy commodity futures in the year 2019.

Table 2 shows the detailed sample information of the selected commodities for the study. The study used the daily closing futures price of gold, silver, aluminum, copper, lead, nickel, zinc, crude oil, and natural gas traded at MCX. According to Table 3, MCX has the highest share of the total value of trade (from 63.53% to 86.64%) among commodity exchanges in India over the period from 2006 to 2018. Hence, futures prices of various commodity contracts are selected from MCX. The study selected commodities based on each commodity's share in the total trade value in MCX and other exchanges. As well, MCX has the highest percentage of the total value of trade for commodities: gold, silver, aluminum, copper, lead, zinc, crude oil, and natural gas. The total value of traded contracts for these commodities' trade was collected from the Securities and Exchange Board of India (SEBI), the market regulator for the commodity futures market. Metal commodity futures was introduced by the MCX in 2005, whereas bullions were introduced in 2003. One year gap was given in the sampling period to avoid high fluctuation in the dataset.

The futures data include near month series of the daily closing price for the selected commodities. Continuous futures price series data for the selected commodities are collected from the Bloomberg database. Return series is defined as the first difference of natural logarithmic spot price (S_t) and the futures price (F_t) at the level. These are mentioned as follows:

$$\begin{aligned} \Delta S_t &= R_{st} = \ln(S_t) - \ln(S_{t-1}), \\ \Delta F_t &= R_{ft} = \ln(F_t) - \ln(F_{t-1}). \end{aligned} \tag{1}$$

The relationship between spot and futures prices can be explained through the cost-of-carry model and the efficient market hypothesis [64]. If spot price (S_t) and futures price (F_t) series are integrated or I (1), we can estimate the

Table 1: Summary of earlier studies regarding price discovery in commodity futures markets.

Author(s)	Period	Variables	Econometric methods	Empirical outcomes
		Indian commodity markets		
Vijayakumar [19]	January 2017–March 2020	Cardamom	Johansen cointegration, vector error correction model, Granger causality, and regression with dummy variables	Cardamom e-auction prices exhibit a negative association with cardamom futures but a positive relation with spot prices
Pradhan, Hall, and Toit [28]	2009–2020	Commodities (aluminum, copper, crude oil, gold, nickel, and silver) and indices (agriculture, livestock, and precious metals)	ARDL bounds testing	Long-run unidirectional causality from spot to futures prices for aluminum, copper, and silver but short-run bidirectional, unidirectional, and neutrality between spot and futures prices
Rout, Das, and Rao [16]	January 2010-December 2015	Chana, chilli, jeera, soya bean, and turmeric.	Causality test, error correction model, EGARCH, and parametric VaR	Volatility spreads from the spot market to the futures market
Nair [22]	January 2008-December 2019	Aluminium, Copper, Nickel, and Zinc	Johansen test, error correction model, and Granger causality	Metals' futures prices are heavily weighted in predicting futures spot market prices
Nair [18]	January 2004–December 2019	Pepper, cardamom, and natural rubber	Cointegration-ECM-GARCH framework	Price discovery in commodity futures markets is efficient
Mohanty and Mishra [17]	October 2015–March 2016	Castor seed, cotton oil cake, rape mustard seed, soybean, refined soya oil, crude palm oil, jeera, chana (chickpea), and turmeric	Variance ratio tests	Agricultural commodity futures markets in India are inefficient in the short term both before and after merger
Manogna and Mishra [15]	2010–2020	Oil seeds (cotton seed, castor seed, soybean seed, rape mustard seed), spices (turmeric, jeera coriander), and grains (guar seed, chana)	Granger causality, vector error correction model (VECM) and exponential generalized autoregressive conditional heteroskedasticity (EGARCH)	Price discovery exists in all of the commodities studied, with the futures market outperforming the spot market in six of them: soybean seed, coriander, turmeric, castor seed, guar seed, and chana
Kaur and Singh [21]	2007–2016	Gold exchange traded funds	Johansen test of cointegration, fully modified ordinary least squares, Toda-Yamamoto test of causality	Spot and futures price movements have been found to lead those of exchange traded funds
Jena, Tiwari, Hammoudeh, and Roubaud [27]	2005–2017	Bullion commodities (gold and silver), and energy commodities (Brent crude oil and natural gas)	Causality-in-quantiles test	Because of its informational efficiency, the foreseeability of the futures market is high in the normal market and declines when the spot market enters severe bearish and bullish situations
Bhaumik, Karanasos, and Kartsaklas [24]	1995–2007	NSE index	Bivariate ARFI-FIGARCH	The integration of futures trading lessens spot variability
Inoue and Hamori [23]	January 2006–March 2011	The spot index (MCXSCOMDEX) and futures index (MCXCOMDEX)	Dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS)	The futures market for commodities appears to be efficient
Joseph, Sisodia, and Tiwari [25]	January 2008–December 2012	Gold, silver, crude oil, natural gas, aluminium, copper, chana, and soybean	Granger causality test and causality analysis in the frequency domain	Almost all of the commodities selected have one-way relationships from futures to spot

Table 1: Continued.

Author(s)	Period	Variables	Econometric methods	Empirical outcomes
Mahalik, Acharya, and Babu [50]	June 2005–December 2008	Agriculture futures price index (LAGRIFP), energy futures price index (LENERGYFP), and aggregate commodity index (LCOMDEXFP)	Vector error correction model (VECM) and bivariate exponential Garch model (EGARCH)	Futures commodity markets exert a leading role and offer effective price discovery in the spot commodity market
Ali and Gupta [20]	2004–2007	Wheat, rice, maize, chickpea, black lentil, red lentil, guar seed, pepper, cashew, castor seed, soybean, and sugar	Johansen cointegration analysis, and Granger causality	Most agricultural commodities exhibit a long-term connection among futures and spot prices
Worldwide commodity markets				
Jian, Li, and Zhu [51]	April 2015–April 2018	CSI300, SSE50, and CSI500	Skewness-dependent multivariate conditional autoregressive value at risk model (SDMV-CAViaR)	Severe risk overflows in both directions among the Chinese stock index futures and spot markets
Chen and Tongurai [52]	April 2015–March 2020	Copper, aluminium, zinc, lead, nickel, and tin	Forecast error variance decomposition	Chinese futures markets for base metals tend to produce more spillover effects than spot markets
Yu, Ding, Sun, Gao, Jia, Wang, and Guo [53]	July 2003–December 2019	Shanghai metal exchange copper spot prices, COMEX copper futures prices, LME copper futures prices, and Shanghai futures exchange copper futures prices	Wavelet decomposition	The futures markets in New York and London are more associated with the Chinese spot market than the Shanghai futures market
Ausloos, Zhang, and Dhesi [54]	2007–2013	CSI-300 index (China-Shanghai-Shenzhen-300-Stock index) and CSI-300 index futures (CSI-300-IF)	TGARCH, Granger causality, and regression analysis	Two-way Granger causality among futures and spot market in China
Go and Lau [55]	January 2000–July 2016	Crude palm oil spot and futures prices in Malaysian currency	Variance ratio tests	During the bear market time span, spot and futures prices are strongly linked
Kirkulak-Uludag and Lkhamazhapov [56]	2008–2013	Russian spot and three-month futures gold prices	Corrected dynamic conditional correlation model	The conditional correlation among spot and futures gold returns is significantly greater

Source: authors' own work.

Johansen test of multivariate cointegration test [65, 66] for establishing long-run equilibrium and vector error correction model [67] for the direction of short-run causality. This can be expressed as follows:

$$F_t = \beta_0 + \beta_1 S_t + \varepsilon_{ft}, \tag{2}$$

$$S_t = \alpha_0 + \alpha_1 S_t + \varepsilon_{st}, \tag{3}$$

where $S_t = \mathrm{Ln}(S_t)$ and $F_t = \mathrm{Ln}(F_t)$ parameters are represented by α and β, and $\varepsilon_{ft}, \varepsilon_{st}$ represent the deviations from equilibrium relationship between two prices. Johansens's method of cointegration can be explained through vector autoregressive (VAR) representation for (2) and (3).

$$X_t = A_0 X_{t-1} + A_1 X_{t-2} + A_k X_{t-k} + \varepsilon_t, \tag{4}$$

where $X_t = \begin{pmatrix} S_t \\ F_t \end{pmatrix}_{2\times1} \begin{bmatrix} S_t & F_t \end{bmatrix}'$ vector represents the natural logarithm of spot and futures price, respectively; $\varepsilon_t = \begin{pmatrix} \varepsilon_{st} \\ \varepsilon_{Ft} \end{pmatrix}_{2\times1}$ is a vector of $\begin{bmatrix} \varepsilon_{st} & \varepsilon_{ft} \end{bmatrix}'$ error terms of S_t, F_t, and $\varepsilon_{st}, \varepsilon_{ft} \sim (WN(0, \sigma^2))$; $A_0 = \begin{pmatrix} a_0 \\ a_0 \end{pmatrix}_{2\times1}$ represents a vector of constant, and $A_1 = \begin{pmatrix} a_{1,11} & a_{1,12} \\ a_{1,21} & a_{1,22} \end{pmatrix}_{2\times2}$ represents the parameter matrix. Equation (4) can be transformed into the following forms:

$$\begin{aligned} \Delta X_t &= A_0 + \Pi X_{t-k} + \Gamma_1 \Delta X_{t-1} + \cdots + \Gamma_{k-1} \Delta X_{t-k+1} + \varepsilon_t \\ \Delta X_t &= A_0 + \Pi X_{t-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-k+1} + \varepsilon_t, \end{aligned} \tag{5}$$

where $\Pi = \sum_{j=1}^{k} A_j - I$ and $\Gamma_i = \sum_{j=1}^{i} A_j - I$.

The rank (r) test $(r = 0, 1, \ldots, g-1)$ of Π matrix gives the number of cointegration relations between the variables. If the rank of Π matrix is $1 < \mathrm{rank}(\Pi) < g$, then $\Pi = \alpha_{g\times r} * \beta_{r\times g}{}' = \begin{pmatrix} \alpha_{11} \\ \alpha_{12} \end{pmatrix} \begin{pmatrix} \beta_{11} & \beta_{12} \end{pmatrix}$, β matrix gives the cointegrating parameters (β_1, β_2), and α matrix gives the adjustment parameters (α_1, α_2). Johansen's method proposes trace $\lambda_{\mathrm{Trace}}(r)$ and likelihood ratio tests for identifying

Table 2: Sample details.

Group	Commodity	Observations	Start date	End date	Q/B	Trading unit
Bullion	Gold	3996	6-Feb-06	31-Dec-19	10 gm	1 kg
	Silver	4166	26-May-05	31-Dec-19	1 kg	30 kg
Metal	Aluminum	3953	4-Jan-06	31-Dec-19	1 kg	5 tons
	Copper	1462	14-Feb-06	29-Nov-19	1 kg	1 mt
	Lead	3525	2-Jul-07	31-Dec-19	1 kg	5 tons
	Nickel	3673	8-Feb-07	31-Dec-19	1 kg	250 kg
	Zinc	3864	2-May-06	31-Dec-19	1 kg	5 tons
Energy	Crude oil	3990	2-Jan-06	18-Dec-19	1 barrel	100 barrel
	Natural gas	3827	20-Oct-06	31-Dec-19	mmbtu	1250 mmbtu

Note. (i) Q/B and T.U. refers to quotation per base value and trading unit. (ii) Trading unit for gold, silver, and nickel is expressed in kilogram, whereas for Aluminum, lead, and zinc, it is in tons. Trading unit of copper refers to million tons. Similarly, for crude oil and natural gas, these are barrel and mmbtu, respectively.

Table 3: Commodity wise total value of trade (%) in Multi Commodity Exchange Limited (MCX).

Group	Commodity	2006	2010	2015	2017	2019
Bullion	Gold	88.83	94.58	100.00	99.40	97.15
	Silver	87.28	97.48	98.75	99.79	100.00
Metal	Aluminum	75.83	100.00	91.97	85.22	89.37
	Copper	99.98	100.00	100.00	99.31	99.80
	Lead	0.00	100.00	99.21	98.06	96.73
	Zinc	99.62	100.00	99.72	97.00	97.65
Energy	Crude oil	100.00	100.00	98.46	99.72	90.16
	Natural gas	100.00	100.00	100.00	100.00	100.00

Source: compiled from Fortnightly Market Review, Forward Market Commission and SEBI, India (2005–2019).

and estimating the number of cointegrating vectors. The tests can be defined as follows:

$$\text{Trace Statistics: } \lambda_{\text{Trace}}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \widehat{\lambda}_i\right). \quad (6)$$

λ_{Trace} test statistics tests the null hypothesis of the number of cointegrating vector (r) s against the alternative hypothesis $(r+1)$.

$$\text{Maximum Eigenvalue statistics}: \lambda_{\text{Max}}(r, r+1) = -T \ln\left(1 - \widehat{\lambda}_{r+1}\right). \quad (7)$$

λ_{Trace} test statistics tests the null hypothesis of the number of cointegrating vector (r) s against the alternative hypothesis (r).

A vector error correction model (VECM) exists for a set of cointegrated variables (Engle and Granger [67], which can be expressed in a bivariate case with lag 1 as follows:

$$\begin{pmatrix} \Delta F_t \\ \Delta S_t \end{pmatrix} = \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} + \begin{pmatrix} \Gamma_{11}\Gamma_{12} \\ \Gamma_{21}\Gamma_{22} \end{pmatrix} \begin{pmatrix} \Delta F_{t-1} \\ \Delta S_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_f \\ \alpha_s \end{pmatrix} (F_{t-1} - \beta_2 S_{t-1}) + \begin{pmatrix} \varepsilon_{ft} \\ \varepsilon_{st} \end{pmatrix}. \quad (8)$$

For the futures market to error correction, $\alpha_f < 0$, and similarly, for spot market to error correction, $\alpha_s > 0$. α_f and α_s represent the coefficients of error correction term and it shows short-run adjustment factors. Error correction terms show how fast the disequlibrium error adjusts to the long-run equilibrium path.

After estimating the cointegrating vector and vector error correction model, the Granger causality test [68, 69] can be used to find out the short-run causality and long-run causality between spot and futures price. The vector error correction model (VECM) in (8) can be represented in the more general form for k^{th} order lag as follows:

$$\Delta FP_t = \delta_1 + \sum_{i=1}^{k} \Gamma_{fp,i} \Delta FP_{t-i} + \sum_{i=1}^{k} \Gamma_{sp,i} \Delta SP_{t-i} + \alpha_1 \left(FP_{t-i} - \beta SP_{t-i} \right) + \varepsilon_{fp}, \tag{9}$$

$$\Delta SP_t = \delta_1 + \sum_{i=1}^{k} \Gamma_{sp,i} \Delta SP_{t-i} + \sum_{i=1}^{k} \Gamma_{fp,i} \Delta FP_{t-i} + \alpha_2 \left(FP_{t-i} - \beta SP_{t-i} \right) + \varepsilon_{sp}. \tag{10}$$

The null hypothesis $\begin{pmatrix} \Gamma_{11}\Gamma_{12} \\ \Gamma_{21}\Gamma_{22} \end{pmatrix} (\Delta S_{t-1}) = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$ implies that lagged terms $\begin{pmatrix} \Delta F_{t-1} \\ \Delta S_{t-1} \end{pmatrix}$ can be tested for short-run causality and with standard likelihood ratio test with χ^2 distribution between spot and futures prices expressed as follows:

$$\begin{pmatrix} \Delta F_t \\ \Delta S_t \end{pmatrix} = \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix} + \begin{pmatrix} \Gamma_{11}\Gamma_{12} \\ \Gamma_{21}\Gamma_{22} \end{pmatrix} \begin{pmatrix} \Delta F_{t-1} \\ \Delta S_{t-1} \end{pmatrix} + \begin{pmatrix} \alpha_f \\ \alpha_s \end{pmatrix} \left(F_{t-1} - \beta_2 S_{t-1} \right) + \begin{pmatrix} \varepsilon_{ft} \\ \varepsilon_{st} \end{pmatrix}. \tag{11}$$

The null hypothesis (H_0) for (9) H_0: $\sum_i^k \Gamma_{sp,i} = 0$ implies that the lagged values of ΔSP do not Granger cause ΔFP or there is no short-run causality between futures price and spot price. Similarily, in (10), the null hypothesis H_0: $\sum_i^k \Gamma_{fp,i} = 0$ shows that the lagged values of ΔFP do not Granger cause ΔSP or there is no short-run casusality between spot price and futures price.

5. Results and Discussion

5.1. Descriptive Statistics. Tables 4 and 5 show the descriptive statistics of the selected commodities for spot and futures returns. The average percentage return in the spot market is higher than the futures market for all the commodities. However, the futures return is negative for zinc and natural gas, which implies a downward bias of futures prices in the futures market. The standard deviation is higher in the spot market for all the commodities than that in the futures markets. It also shows that the spot market is highly volatile than the futures market. The spot return's unconditional distributions are negatively skewed for copper, whereas such distributions of the futures return are negatively skewed for gold, silver, aluminum, and zinc. Spot return distribution is platykurtic for gold, silver, lead, and zinc. However, the spot return distribution is leptokurtic for copper, nickel, crude oil, and natural gas. Spot return for aluminum shows the mesokurtic type of distribution. Futures return distribution is leptokurtic for all the commodities except zinc. Minimum spot return varies from −6.44% (for zinc) to −66.65% (for copper), and maximum spot return varies from 13.19% (for gold) to 82.70% (for natural gas), as shown in Table 4. Similarly, minimum futures return varies from −6.33% (for copper) to −15.90% (for silver), and maximum futures return varies from 5.47% (for gold) to 22.17% (for lead), as shown in Table 5.

5.2. Stationarity Test. Augmented Dickey–Fuller (ADF) test results are presented in Table 6. The test shows that the log of spot and futures prices for level is nonstationary for all the commodities, alike prior studies [15, 16, 18–20, 22, 23, 26, 28, 50]. The null hypothesis of nonstationary is statistically not significant for both the price series in the level. However, the null hypothesis is statistically significant at 1% level of significance for both the spot and futures prices in difference. Thus, the test indicates that the difference of log spot and futures prices is integrated with order 1 for all the commodities. The result of the unit root test directs to proceed for the cointegration analysis, where the first condition, i.e., both the series, must be nonstationary in level and integrated of order one for the Johansen–Juselius (J-J) test needs to be satisfied.

5.3. Granger Causality Test. Before estimating the cointegration test in vector autoregressive (VAR) framework, the Granger causality test is conducted to know if any unidirectional or bidirectional causality relationship exists between spot and futures prices, in line with earlier research [15, 18–20, 22]. Granger causality test is estimated following the equations (10) and (11). The estimation results from the Granger causality test are presented in Table 7. The null hypothesis that spot return does not Granger cause futures return is rejected for gold, silver, aluminum, lead, nickel, zinc, and crude oil. It implies that the spot returns cause futures returns in these commodities. The null hypothesis cannot be rejected for copper and natural gas. It implies that spot return does not cause futures return for copper and natural gas. The null hypothesis that futures return does not Granger cause spot return is rejected for all the commodities. Therefore, futures return Granger causes spot returns for all the commodities. Granger causality test suggests a bidirectional causality relationship between spot and futures prices for gold, silver, aluminum, lead, nickel, zinc, and crude oil. However, futures return does not Granger cause the spot return for copper and natural gas. As the Granger test suggests bidirectional causality between spot and futures prices for most of the commodities, there is a need to explore their meaningful relationship in the long run and short run using the J-J cointegration test followed by the estimation of a dynamic VECM.

Table 4: Descriptive statistics of selected commodities for spot return.

Group	Commodity	Mean	Std. Dev	Skewness	Kurtosis	Min	Max	J-B stat
Bullion	Gold	0.0183	0.0199	0.2761	−2.3658	−0.0680	0.1319	44.4369
	Silver	0.0338	0.0284	0.2558	−2.5279	−0.0835	0.1612	34.8346
Base metals	Aluminum	0.0290	0.0247	0.3915	0.3661	−0.0822	0.1703	758.5985
	Copper	0.0134	0.0526	−3.2404	41.2291	−0.6665	0.2538	1995.4000
	Lead	0.0198	0.0332	0.1312	−1.7161	−0.1095	0.1692	77.1338
	Nickel	0.0231	0.0392	0.5778	1.1388	−0.1159	0.3037	918.3396
	Zinc	0.0288	0.0307	0.4878	−1.6323	−0.0644	0.1575	168.4567
Energy	Crude oil	0.0337	0.0491	1.9676	5.8151	−0.0952	0.4251	5898.1310
	Natural gas	0.0790	0.1116	2.8257	7.6306	−0.0912	0.8271	7752.7000

Table 5: Descriptive statistics of selected commodities for futures return.

Group	Commodity	Mean	Std. Dev	Skewness	Kurtosis	Min	Max	J-B stat
Bullion	Gold	0.0007	0.0104	−0.4798	3.3165	−0.0800	0.0547	2550.9430
	Silver	0.0010	0.0153	−0.8739	8.4257	−0.1591	0.0880	9547.0380
Base metals	Aluminum	0.0002	0.0146	−0.7620	6.9756	−0.1561	0.0587	6458.7260
	Copper	0.0005	0.0145	0.5425	2.0853	−0.0633	0.1060	1652.9410
	Lead	0.0003	0.0227	0.8976	6.7044	−0.1144	0.2218	4343.0010
	Nickel	0.0000	0.0226	0.2799	0.1735	−0.1013	0.1315	516.9168
	Zinc	−0.0001	0.0195	−0.0179	−1.0128	−0.0861	0.0832	235.8748
Energy	Crude oil	0.0004	0.0167	0.0552	0.4974	−0.0872	0.1078	776.1763
	Natural gas	−0.0002	0.0234	1.0416	4.5081	−0.0892	0.1917	3249.1260

Table 6: Unit root test of spot and futures prices (level and difference) for the selected commodities.

Group		Levels (log)			First difference (log)			
	Commodity	Constraint	Spot	Future	Constraint	Spot	Future	Integration
Bullion	Gold	I and T	−3.01	−2.90	I	−10.48	−10.42	I (1)
	Silver	I and T	−1.72	−2.12	I	−10.67	−10.22	I (1)
Base metals	Aluminum	I and T	−1.85	−1.81	I	−10.37	−10.77	I (1)
	Copper	I and T	−1.90	−2.15	None	−11.54	−8.49	I (1)
	Lead	I	−1.67	−1.79	None	−9.74	−9.71	I (1)
	Nickel	I	−1.89	−1.73	I and T	−11.26	−10.84	I (1)
	Zinc	I	−1.22	−1.16	None	−10.69	−10.50	I (1)
Energy	Crude oil	I and T	−1.76	−1.80	None	−12.37	−10.92	I (1)
	Natural gas	I	−2.20	−2.05	None	−10.12	−10.27	I (1)

Note. The Fuller critical values for ADF test at 1%, 5%, and 10% are -3.43, −2.86, −2.57, respectively for constant. The Fuller critical values for ADF test at 1%, 5%, and 10% are -3.96, −3.41, and −3.12, respectively for constant + time trend (denoted by I and T). The Fuller critical values for ADF test at 1%, 5%, and 10% are −2.58, −1.95, and −1.62, respectively for no constant or time trend (denoted by none).

Table 7: Granger causality test of spot and futures returns for the selected commodities.

Group	Commodity	Spot does not Granger cause futures		Futures does not Granger cause spot	
		F-stat	*P*-value	F-stat	*P*-value
Bullion	Gold	6.052	0.001	175.114	0.001
	Silver	2.193	0.031	140.548	0.001
Base metals	Aluminum	9.254	0.001	23.913	0.001
	Copper	0.391	0.892	62.022	0.001
	Lead	5.235	0.001	37.201	0.001
	Nickel	3.135	0.001	46.284	0.001
	Zinc	3.164	0.001	69.612	0.001
Energy	Crude oil	3.542	0.001	116.842	0.001
	Natural gas	0.781	0.592	76.021	0.001

Note. Spot and futures represent spot return and futures return, respectively. p value (0.001) refers to the significance at 1% level.

5.4. Johansen and Juselius (J-J) Cointegration Analysis. Following the stationarity test results of the previous section, the J-J cointegration test is estimated for the spot and futures prices, which are integrated of order one. Identification of the cointegrating relationship among the variables is important, as the VAR model in the first difference is misspecified for the two nonstationary variables, which are cointegrated. After identifying the cointegration relationship(4), VAR will include residuals from the vectors (lagged one period) in the VECM (Engle and Granger, 1987). The J-J cointegration test is estimated by following the Johansen and Juselius (1990) method. The results are presented in Table 8.

λ_{trace} test rejects the null hypothesis of no cointegrating vectors $(r = 0)$ at 1% significance level for silver, aluminum, copper, lead, nickel, and zinc, and it also rejects the same at 5% level for crude oil. Hence, it accepts the null hypothesis of more than zero cointegrating vectors. λ_{trace} test accepts the null of no cointegrating vector in the case of gold and natural gas. It also accepts the $(r \leq 1)$ cointegrating vector's null hypothesis against the alternative hypothesis of more than one cointegrating vectors $(r > 1)$ for silver, aluminum, copper, lead, nickel, and zinc. Similarly, $\lambda_{\max}$ test rejects the null hypothesis of no cointegrating vectors $(r = 0)$ at 1% level of significance for silver, aluminum, copper, lead, nickel, zinc, and crude oil. So, it accepts the alternative hypothesis of one cointegrating vector $(r = 1)$. $\lambda_{\max}$ test accepts the null hypothesis of one cointegrating vector $(r = 1)$ against the null hypothesis of two cointegrating vector $(r = 2)$. Both λ_{trace} and $\lambda_{\max}$ tests suggest the presence of one cointegrating vector for silver, aluminum, copper, lead, nickel, zinc, and crude oil. The tests reject the presence of any cointegrating vector for gold and natural gas. Hence, a dynamic VECM is estimated for all those commodities, where there is a presence of a cointegrating relationship between the spot and futures prices.

5.5. Vector Error Correction Model. Results from the estimation of VECM (8) and (9) for spot and futures prices are presented in Tables 9 and 10. Accordingly, the results are interpreted for different commodities separately.

5.5.1. Silver. The coefficient of the error correction term α_s is negative and not significant. It implies that the spot price is not responding to the previous period's equilibrium. α_F is positive, which implies that silver's futures price is responding positively to the previous period's equilibrium. In ECM for spot price, the coefficients are negative and significant up to lag 5. However, the coefficients for the futures price are positive and significant up to lag 5. It shows that lagged spot price has a negative impact, and lagged futures price positively impacts the spot price. In ECM for the futures price, the spot price coefficients positively impact futures prices up to lag 5, whereas lagged futures price has a negative impact on the current futures price. Spot price at lag 1 has the highest impact on the current futures price than the higher lags. ECM result implies that the previous day spot prices have a positive impact on the futures price. Thus, it is established that the futures market leads the spot market and not vice versa in the price discovery process.

5.5.2. Aluminium. The error correction term's coefficient is negative and statistically not significant at 5% level of significance. In ECM for spot price, lagged spot price coefficients up to lag 5 are negative and statistically significant. It is found that the coefficients for both spot and futures prices are declining throughout the lag. It means that the previous spot price at lag 1 has a more negative impact on the current spot price than other previous prices at higher lags. Futures price coefficients are positively influencing the current spot price. In ECM for the futures price, α_F is positive and statistically significant at 1% level. It shows that the futures price's short-run deviations would be adjusted in an upward direction towards the long-run equilibrium. The coefficients for lagged spot prices positively impact the current futures price, and the coefficients of lagged futures prices have a negative impact on the current futures price. The results suggest that the futures market leads to the spot market, and the spot market does not lead to the futures market in price discovery.

5.5.3. Copper. The coefficient of the error correction term α_s is negative and statistically significant at 5% level. When α_s is negative and statistically significant, spot price corrects the deviations from the long-run equilibrium. So, if the actual equilibrium value is high, the negative error correction term will reduce it, and if the equilibrium value is too low, the error correction term will raise it. The spot price is responsive to the previous period's equilibrium error. In ECM for the spot price, the lagged spot price coefficients up to lag 5 are negative and statistically significant at 1% level, whereas lagged futures price coefficients are positive. ECM for the futures price (11) is not statistically significant. Therefore, the impact of the futures price in adjusting the error towards long-run equilibrium can be ruled out.

5.5.4. Lead. The coefficient of the error correction term α_s is negative and statistically not significant. In ECM for spot price, the spot price coefficients up to lag 6 are negative and statistically significant at 1% level. Previous spot price up to lag 8 has an impact on the current spot price, and the declining effect of the lagged spot price varies from −0.44 in lag 1 to -0.21 in lag 8. Futures price coefficients up to lag 8 affect the current spot price positively. In ECM for the futures price, α_F is positive and statistically significant at 5% level. It shows that the futures price's short-run deviations would be adjusted in an upward direction towards the long-run equilibrium. Coefficients for lagged spot prices up to lag 8 have a positive impact on the current futures price. Similarly, the coefficients for lagged futures prices up to lag 8 negatively affect the current futures price. The results also show

Table 8: Johansen and Juselius cointegration rank test of spot and futures prices.

Group	Commodity	Lag length	Maximum trace value		Maximum eigen value		Remark
			H_0: rank = 0 vs H_1: rank = 1	H_0: rank = 1 vs H_1: rank = 2	H_0: rank = 0 vs H_1: rank = 1	H_0: rank = 1 vs H_1: rank = 2	
Bullion	Gold	10	18.84	2.44	14.40	2.44	NS
	Silver	6	37.22	3.65	33.57	3.65	1
Base metals	Aluminum	6	60.95	2.87	58.08	2.87	1
	Copper	7	72.45	3.66	68.80	3.66	1
	Lead	9	55.10	3.37	51.73	3.37	1
	Nickel	10	29.77	4.31	25.46	4.31	1
	Zinc	8	51.04	2.85	48.19	2.85	1
Energy	Crude oil	10	23.50	3.65	20.85	3.65	1
	Natural gas	4	14.90	3.08	11.81	3.08	NS

Note. Critical values of λ_{trace} ($r = 0$) for 1%, 5%, and 10% significance levels are 24.6, 19.96, and 17.85, respectively. Critical values of λ_{trace} ($r = 1$) for 1%, 5%, and 10% are 12.97, 9.24, and 7.25, respectively. Critical values of λ_{Max} ($r = 0$) for 1%, 5%, and 10% are 20.2, 15.67, and 13.75, respectively. Critical values of λ_{Max} ($r = 1$) for 1%, 5%, and 10% are 12.97, 9.27, and 7.52, respectively. AIC lag selection criteria are used for the estimation.

Table 9: Vector error correction model for spot price of the selected commodities.

Coefficients	Silver	Aluminum	Copper	Lead	Nickel	Zinc	Crude oil
α_s	−0.01	−0.06*	−0.19**	−0.15*	−0.07*	−0.13***	−0.02***
	(−0.98)	(−2.44)	(−8.34)	(−2.54)	(−2.17)	(−3.45)	(−1.39)
ΔS_{t-1}	−0.43***	−0.25***	−0.25***	−0.44***	−0.48***	−0.57***	−0.43***
	(−14.81)	(−8.08)	(−9.33)	(−10.34)	(−11.45)	(−15.68)	(−14.51)
ΔS_{t-2}	−0.32***	−0.19***	−0.52***	−0.42***	−0.38***	−0.52***	−0.27***
	(−10.20)	(−5.65)	(−19.63)	(−8.38)	(−7.76)	(−11.10)	(−8.31)
ΔS_{t-3}	−0.23***	−0.17***	−0.24***	−0.35***	−0.28***	−0.40***	−0.17***
	(−7.09)	(−4.87)	(−8.05)	(−6.18)	(−5.19)	(−8.33)	(−4.97)
ΔS_{t-4}	−0.16***	−0.13***	−0.30***	−0.37***	−0.33***	−0.35***	−0.05
	(−5.09)	(−3.61)	(−10.93)	(−6.15)	(−6.02)	(−6.90)	(−1.39)
ΔS_{t-5}	−0.06*	−0.11**	−0.23***	−0.32***	−0.25***	−0.26***	−0.04
	(−2.26)	(−2.96)	(−8.71)	(−5.04)	(−4.35)	(−5.01)	(−1.16)
ΔS_{t-6}	—	—	−0.23***	−0.23***	−0.20***	−0.21***	−0.04
	—	—	(−8.97)	(−3.47)	(−3.43)	(−4.12)	(−1.06)
ΔS_{t-7}	—	—	—	−0.18	−0.15	−0.21	−0.17
	—	—	—	(−2.79)	(−2.58)	(−4.46)	(−5.05)
ΔS_{t-8}	—	—	—	−0.21**	−0.29***	—	−0.12***
	—	—	—	(−3.25)	(−5.31)	—	(−3.49)
ΔS_{t-9}	—	—	—	—	−0.15**	—	−0.14***
	—	—	—	—	(−3.08)	—	(−4.98)
ΔF_{t-1}	0.68***	0.39***	0.11***	0.73***	0.75***	0.78***	0.88***
	(28.59)	(11.65)	(17.84)	(14.64)	(16.80)	(20.19)	(26.89)
ΔF_{t-2}	0.31***	0.22***	0.23***	0.51***	0.52***	0.66***	0.35***
	(9.59)	(5.86)	(3.43)	(8.54)	(9.51)	(13.57)	(8.41)
ΔF_{t-3}	0.28***	0.11**	0.57***	0.39***	0.32***	0.49***	0.22***
	(8.62)	(2.95)	(8.28)	(5.99)	(5.35)	(8.97)	(5.06)
ΔF_{t-4}	0.21***	0.17***	0.17*	0.37***	0.30***	0.39***	0.14***
	(6.35)	(4.44)	(2.49)	(5.28)	(4.73)	(6.75)	(3.31)
ΔF_{t-5}	0.12***	0.09***	0.35*	0.33***	0.31***	0.28***	0.03
	(3.84)	(2.21)	(5.12)	(4.47)	(4.74)	(4.69)	(0.71)
ΔF_{t-6}	—	—	0.16*	0.21**	0.24***	0.22***	0.07
	—	—	(2.31)	(2.74)	(3.66)	(3.68)	(1.64)
ΔF_{t-7}	—	—	—	0.15*	0.16*	0.21***	0.10
	—	—	—	(1.97)	(2.28)	(3.17)	(2.36)
ΔF_{t-8}	—	—	—	0.28***	0.23***	—	0.13***
	—	—	—	(3.72)	(3.74)	—	(3.01)
ΔF_{t-9}	—	—	—	—	0.23***	—	0.12**
	—	—	—	—	(3.89)	—	(2.89)
$\overline{R}^2$	0.33	0.09	0.33	0.19	0.22	0.23	0.35
F − Stat	77.43	14.17	55.63	14.55	17.26	29.96	41.20
LM (χ^2)	32.07	25.29	29.06	54.07	51.16	11.91	51.25
	(0.13)	(0.39)	(0.41)	(0.54)	(0.11)	(0.16)	(0.11)

Note. Figures in parenthesis refer to respective t-stat for the coefficients.***,**, and* represent statistical significance at 1%, 5%, and 10%, respectively. Statistical significance of coefficients is considered at 5% level of significance. F-statistics is significant at 1% level for all the commodities.LM (χ^2) value shows the chi-square value of Breusch–Godfrey LM test for serial autocorrelation.

Table 10: Vector error correction model for futures price of the selected commodities.

Coefficients	Silver	Aluminum	Copper	Lead	Nickel	Zinc	Crude oil
α_F	0.08 ***	0.10 ***	0.01	0.17 **	0.05	0.07 *	0.04 **
	(4.30)	(4.50)	(0.23)	(3.19)	(1.63)	(2.04)	(3.01)
ΔS_{t-1}	0.14 ***	0.20 ***	−0.02	0.22 ***	0.15 ***	0.12 ***	0.08 **
	(4.05)	(7.34)	(−0.03)	(6.03)	(3.90)	(3.54)	(3.16)
ΔS_{t-2}	0.08 *	0.16 ***	0.01	0.18 ***	0.15 **	0.10 *	0.08 **
	(2.15)	(5.32)	(1.11)	(4.29)	(3.21)	(2.48)	(2.58)
ΔS_{t-3}	0.08 *	0.13 ***	0.07	0.18 ***	0.17 ***	0.13 **	0.08 **
	(1.97)	(4.18)	(0.23)	(3.73)	(3.42)	(2.78)	(2.75)
ΔS_{t-4}	0.06	0.13 ***	0.04 *	0.15 **	0.08	0.16 ***	0.11 ***
	(1.54)	(4.10)	(1.02)	(3.02)	(1.62)	(3.45)	(3.66)
ΔS_{t-5}	0.10 **	0.14 ***	0.03	0.17 **	0.12 *	0.17 ***	0.12 ***
	(3.16)	(4.17)	(0.62)	(3.22)	(2.16)	(3.54)	(3.85)
ΔS_{t-6}	—	—	0.04	0.18 **	0.08	0.12 **	0.11 ***
	—	—	(0.05)	(3.17)	(1.56)	(2.61)	(3.40)
ΔS_{t-7}	—	—	—	0.15 **	0.07	0.02	−0.01
	—	—	—	(2.66)	(1.27)	(0.52)	(−0.258)
ΔS_{t-8}	—	—	—	0.21 ***	−0.09 *	—	0.05 *
	—	—	—	(3.71)	(−1.86)	—	(1.69)
ΔS_{t-9}	—	—	—	—	0.01	—	0.04
	—	—	—	—	(0.04)	—	(1.63)
ΔF_{t-1}	−0.07 *	−0.14 ***	−0.02	−0.08 *	−0.04	−0.05	0.02
	(−2.51)	(−4.61)	(−0.76)	(−1.98)	(−0.86)	(−1.45)	(0.65)
ΔF_{t-2}	−0.10 **	−0.15 ***	0.03	−0.15 **	−0.12 *	−0.08 *	−0.13 ***
	(−2.77)	(−4.43)	(1.09)	(−2.91)	(−2.36)	(−1.85)	(−3.55)
ΔF_{t-3}	−0.03	−0.12 ***	0.02	−0.21 ***	−0.23 ***	−0.15 **	−0.09 *
	(−0.89)	(−3.57)	(0.81)	(−3.73)	(−4.11)	(−2.86)	(−2.33)
ΔF_{t-4}	−0.09 *	−0.11 **	0.03	−0.17 **	−0.16 **	−0.15 **	−0.09 *
	(−2.25)	(−3.01)	(0.95)	(−2.88)	(−2.76)	(−2.89)	(−2.18)
ΔF_{t-5}	−0.07 *	−0.14 ***	0.07	−0.22 ***	−0.06	0.20 ***	−0.13 **
	(−1.89)	(−3.89)	(2.32)	(−3.50)	(−0.96)	(−3.53)	(−3.26)
ΔF_{t-6}	—	—	0.03	−0.22 ***	−0.09	−0.19 ***	−0.12 **
	—	—	(1.18)	(−3.39)	(−1.49)	(−3.49)	(−2.95)
ΔF_{t-7}	—	—	—	−0.20 **	−0.09	−0.09 *	−0.09 *
	—	—	—	(−3.04)	(−1.47)	(−1.85)	(−2.34)
ΔF_{t-8}	—	—	—	−0.19 **	0.01	—	−0.06
	—	—	—	(−2.49)	(0.03)	—	(−1.55)
ΔF_{t-9}	—	—	—	—	0.09	—	−0.04
	—	—	—	—	(1.59)	—	(−1.08)
$\overline{R}^2$	0.02	0.04	0.01	0.06	0.04	0.03	0.04
F − Stat	3.44	7.20	1.35	3.98	3.45	2.47	2.96
LM (χ^2)	32.07	25.29	29.06	54.07	51.16	11.91	51.25
	(0.13)	(0.39)	(0.41)	(0.54)	(0.11)	(0.16)	(0.11)

that the futures market leads spot market in price discovery and not vice versa.

5.5.5. Nickel. The coefficient of the error correction term α_s s negative and statistically not significant. In ECM for spot price, the spot price coefficients up to lag 9 are negative and statistically significant at 1% level. Previous spot prices up to lag 9 impact the current spot price, and the declining effect of the lagged spot price varies from -0.48 in lag 1 to −0.15 in lag 9. Futures price coefficients up to lag 9 affect positively the current spot price. In ECM for the futures price, α_F is positive and statistically not significant. So, it suggests that short-run deviations of the futures price are not adjusting towards the long-run equilibrium. The coefficients for lagged spot prices up to lag 3 have a positive impact on the current futures price. Similarly, the lagged futures price's coefficients up to lag 6 have a negative impact on the current futures price. Thus, the results show that both the spot and futures markets are not adjusting in short-run deviations towards long-run equilibrium.

5.5.6. Zinc. The coefficient of the error correction term α_s is negative and statistically significant. When α_s is negative and statistically significant, spot price corrects the deviations from the long-run equilibrium. The spot price is responsive to the previous period's equilibrium error. In ECM for the spot price, coefficients up to lag 5 are negative and statistically significant. The result shows that coefficients for both spot and futures prices are declining for lag. It means that the spot price at lag 1 has a more negative impact on the current

spot price than the spot price of higher lags. Futures price coefficients up to lag 6 are positively influencing the current spot price. In ECM for the futures price, α_F is positive and statistically not significant. It implies that short-run deviations of the futures price are not adjusting towards the long-run equilibrium. The coefficients for lagged spot prices up to lag 6 positively impact the current futures price. Lagged futures price coefficients at lag 1 and lag 2 are statistically not significant. However, lagged futures price coefficients from lag 3 to lag 6 have a negative impact on the current futures price. Thus, it can be established that the spot market leads to the futures market and not vice versa.

5.5.7. Crude Oil. The coefficient of the error correction term α_s is negative and statistically significant. When α_s is negative and statistically significant, the spot price corrects the deviations from the long-run equilibrium and responsive to the previous period's equilibrium error. In ECM for the spot price, coefficients for lagged spot price up to lag 3 have a negative impact on the current spot price. Lagged futures prices up to lag 4, and at lag 8 and lag 9 are having a positive impact on the current spot price. Futures price coefficients are positively influencing the current spot price. In ECM for the futures price, α_F is positive and statistically significant at 5% level. It shows that the futures price's short-run deviations would be adjusted in an upward direction towards the long-run equilibrium. The coefficients for lagged spot price up to lag 5 have a positive impact on the current futures price, and the coefficients for lagged futures price at lag 1, lag 5, and lag 6 have a negative effect on the current futures price. Thus, both spot and futures markets contribute to the process of price discovery, as they can adjust to the short-run deviations towards the long-run equilibrium.

VECM regressions for spot and futures prices are significant for silver, aluminum, lead, nickel, zinc, and crude oil. However, the error correction model for the futures price of copper is not statistically significant. $\overline{R}^2$ the error correction model for the spot price (10) is higher than the futures price (11). The results from the model's estimation imply that the error correction term α_s and the lagged futures and spot prices explain the model better than the futures price equation. Breusch–Godfrey LM χ^2 test for serial autocorrelation is conducted to test the null hypothesis of no autocorrelation at the respective lag for all the commodities. Values are not statistically significant for all the commodities, which imply no autocorrelation problem in the dataset for all the commodities. It also confirms that the selected lags for the commodities are appropriate for estimating a vector autoregressive model.

6. Concluding Remarks and Policy Implications

The above empirical findings imply no lead-lag relationship between the spot and futures prices for gold, silver, aluminum, lead, nickel, zinc, crude oil, and natural gas. Market participants can use price as a source of information from both the spot and the futures markets. However, the spot markets do not impact the futures markets for copper and natural gas. The J-J cointegration test reveals that the spot and futures prices move together in a long-run equilibrium path for silver, aluminum, copper, lead, nickel, zinc, and crude oil. The test rejects any evidence of the cointegrating relationship of spot and futures prices for gold and natural gas. This implies the possibility of random walk nature in the spot and futures prices, and arbitrage fails to correct the disequilibrium.

The existence of a cointegrating relationship implies that both the spot and futures markets may have short-run disequilibrium. However, this can be corrected by the arbitrage process. Spot markets play a crucial role in adjusting any short-run disequilibrium error for copper and zinc. However, futures market is more dominant in the case of silver, aluminum, and lead in adjusting the short-run disequilibrium. Both spot and futures markets are responsible for correcting the short-run disequilibrium for nickel and crude oil. As the Indian commodity futures market is growing rapidly, the findings have implications for the various market participants to implement trading and arbitrage strategy. It will also help the policy makers to check the stability of the market.

Policymakers and regulators should highlight the efficiency of futures markets and enhance market participation by effectively applying trading strategies that allow market participants to take advantage of data accessibility [15]. In this regard, the outcomes can assist traders in more accurately estimating price changes, permitting them to confirm when investing and arbitraging opportunities emerge and how long they will persevere in the market [25]. As well, the Indian government should develop its institutional infrastructure to allow for more seamless commodity transactions consistent with market advances [23]. As such, expanded policies and enforcement are required, as well as expanded broker and dealer involvement in the commodities market, the insertion of exotic commodity derivatives, and heightened transparency and disclosure [17]. Besides, through investor awareness campaigns, the SEBI can strive to strengthen public awareness about the latest financial instruments [21].

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Research on the Time-Frequency Spillover Effect of High-Frequency Stock Price and Economic Policy Uncertainty

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Through the construction of wavelet coherence analysis and frequency-domain spillover framework, this paper makes a comparative study of the volatility spillover effects of international economic policy uncertainty (EPU) on China's Shanghai and Hong Kong stock market from a time-frequency perspective. To fully reflect the international EPU, this paper selects China, the United States, Australia, and the United Kingdom and uses the monthly EPU index of these countries and regions. China chooses China's EPU index and Hong Kong's EPU index. At the same time, the 5-minute high-frequency volatility of the Shanghai Composite Index (SSEC) and the Hang Seng Index (HSI) is selected to represent the Shanghai and Hong Kong's stock market, respectively. It is found that there are obvious differences between the EPU and the dependence of the stock market in time domain and frequency domain, and the lead-lag relationship between them has time-varying characteristics. Static and dynamic spillover effects play a dominant role in the analysis of medium- and long-term spillover effects. In particular, the EPU and the risk spillover of the Hong Kong stock market are stronger than those of the Shanghai stock market, and the dynamic frequency-domain net risk spillover between them has frequency characteristics, and there are two-way and asymmetric risk spillovers. This provides a certain reference for policy makers to improve the safety management of financial markets and for market investors to optimize their portfolios.

1. Introduction

The uncertainty of economic policy shows that the economic subject is affected by the impact of economic events, but the future economic situation cannot be accurately predicted. Under the impact of the epidemic of COVID-19 in 2020, the economic uncertainty index of various countries has increased significantly, which has brought a negative impact on China's macroeconomy and enterprise investment behavior to a certain extent. Since the outbreak of the international financial crisis in 2008, the economies of all countries have been affected to varying degrees, and the global economy is developing slowly and showing a trend of recession. In order to promote economic recovery, countries have issued a series of economic policies. However, the economic environment and economic structure are difficult to predict and are complex, and it is difficult to respond quickly to the market economic situation only through market self-regulation. Therefore, the state is more inclined to intervene and regulate domestic "too big to fail" financial institutions directly. Under this background, this paper uses wavelet coherence and the BK spillover index model to explore the volatility spillover effects of the stock market in the past 20 years from the perspectives of time domain and frequency domain, so as to provide a scientific and reasonable basis for dealing with the future international policy uncertainty.

The main purpose of this paper: first, to use wavelet coherence to analyze the volatility spillover effects of EPU of various countries on China's Shanghai and Hong Kong stock market from January 2000 to February 2021 from the perspective of the time domain and frequency domain. This helps market decision makers and market participants to identify the factors that lead to the risk of the stock market. Second, construct a frequency-domain framework to quantitatively analyze the spillover direction and persistence

of international EPU on the stock market. This is helpful for the financial market to carry out scientific and reasonable risk control.

The possible innovation of this paper lies in three aspects: the selection of research perspective, the selection of research objects, and the method of research model. First is the innovation in the choice of research perspective. This paper divides the same frequency band into short-term, medium-term, and long-term segments to explore the spillover effects between them and further analyzes the spillover effects of EPU on the stock market according to specific national conditions and economic events. Second is the innovation in the selection of research objects. This paper uses the EPU index compiled by Baker to quantify the economic uncertainty index, and the stock market selects the Shanghai Composite Index and Hang Seng Index of five-minute high-frequency data to comprehensively investigate the time-frequency spillover effects of EPU on the stock market. Third is the innovation of research model method. The empirical model chooses the more cutting-edge econometric model as the research method. The model chooses the spillover index model based on the generalized spectrum representation, which is improved by the Diebold and Yilmaz spillover index model based on variance decomposition, and captures the static and dynamic time-varying characteristics of the spillover effects of EPU on the stock market by dividing long term, medium term, and short term.

The main contribution of this paper is to compare and analyze the volatility spillover effects of international EPU on Shanghai and Hong Kong stock market from the perspective of time domain and frequency domain. First, this paper makes a comparative study of the volatility spillover effects of the EPU index of representative countries and regions on China's Shanghai and Hong Kong stock market and takes into account the study of international economic policies on China's stock market. In addition, the domestic stock market is divided into inland stock market and offshore stock market for comparative study, using the 5-minute high-frequency realization volatility of Shanghai Composite Index and Hang Seng Index as the research object. We study and analyze the spillover degree of EPU on the stock market to improve the research and analysis. There is little literature in this area, so this paper expands the relevant literature.

Secondly, by using wavelet coherence analysis, this paper reveals the spillover effects of international EPU on the Chinese stock market from the point of view of time domain and frequency domain and captures the time-varying relationship between EPU and the stock market. Furthermore, the construction of a frequency-domain framework focuses on the analysis of the direction and persistence of frequency-domain spillovers between them and compares and analyzes the spillover degree of EPU on the two stock markets. It provides theoretical significance for how to prevent the mainland stock market and the offshore stock market.

Third, this paper adopts the method of the dynamic and static combination when selecting the model and explores the time-varying spillover effects between EPU and the stock market through a rolling window. It mainly studies the impact of the financial things on the economic uncertainty and analyzes the spillover of the impact on the stock market. This will help relevant policymakers to clarify the spillover persistence of EPU on the stock market, to effectively provide targeted suggestions for the Shanghai and Hong Kong stock market, and to help investors avoid risks reasonably.

The main finding of this paper is that this paper selects the Diebold and Yilmaz spillover index model and Baruink spillover index model to analyze the time-varying characteristics of spillover effects from different perspectives of time domain and frequency domain. It is concluded that there are time-varying characteristics between the uncertainty of different economic policies and the spillover of the stock market, and the medium- and long-term spillover effects between the two are dominant. In addition, the study found that the spillover degree of different economic policy uncertainties on the Shanghai stock market is less than that of the Hong Kong stock market, and the Shanghai stock market occupies a dominant position in the spillover between the two, as the main sender of the spillover effect. Hong Kong stock market spillover is between the two as the main receiver.

Based on the above main conclusions, the policy recommendations of this paper are discussed from the perspective of government regulators and investors, respectively. On the one hand, from the perspective of government regulators, first, regulatory departments should closely monitor the changes and direction of the current international economic situation, continue to improve China's financial development policy, and maintain the stable and healthy operation of the market. We keep the RMB exchange rate floating at a stable and balanced level, guard against the risk of abnormal fluctuations, and focus on monitoring abnormal cross-border capital flows. Second, to create a regulatory environment matched with the high-level opening of the capital market, we should strengthen the construction of the basic system of the stock market and further form a legalized and mature stock market. Third, we strengthen the supervision of offshore financial markets and promote the two-way and orderly opening of financial markets. On the other hand, from the perspective of investors, investors should reasonably refer to the relevant market indicators, observe the market situation, and make correct investment decisions. Investors should not only pay more attention to the changes of international economic policies, that is, the occurrence and changes of international economic events, but also combine the frequency characteristics of spillover effects between economic policies and stock markets, taking into account the long-term impact of spillover effects. In order to constantly optimize their own investment portfolio, we improve investment strategies.

The rest of this paper is arranged as follows. Section 2 introduces the literature review. Section 3 introduces the model method used. Section 4 introduces the results of empirical analysis. Section 5 introduces the robustness test carried out. Section 6 summarizes the conclusions and puts forward countermeasures and suggestions.

2. Literature Review

Studying the changes of EPU is of great significance for predicting macroeconomic situations or microeconomic behavior. How to quantify EPU indicators has been the focus of many scholars. Baker et al. [1] used text analysis to develop a new EPU index according to the frequency of newspaper reports and constructed the EPU index of 12 countries, including the United States. This paper also uses the national EPU index compiled by Baker to quantify the national EPU (EPU).

With the quantification and wide application of uncertainty index, more and more scholars apply uncertainty to the process of empirical research. By studying the impact of EPU (EPU) on stock market returns, Antonakakis et al. [2] found that there is a linkage relationship between economic policy uncertainty and the stock market. Pastor and Veronesi [3] built a model to provide advice for government decision-making. The analysis results show that EPU (EPU) will lead to risk premium, and then, corporate financing costs will rise. Li and Yang [4] use China's EPU index to reveal that the increase in EPU will inhibit corporate investment, and this inhibitory effect is more significant due to the impact of the 2008 financial crisis. Gong et al. [5] use the EPU index constructed by Baker to study the impact of policy uncertainty on the corporate leverage ratio. The results show that the increase of EPU will lead to a significant decrease in corporate leverage ratio, and the negative impact is more significant in short-term debt ratio, private, small-scale, and manufacturing enterprises.

In addition, to depict the correlation between markets, pieces of literature use wavelet coherence analysis to capture the dynamic connection between the two. Percival and Walden [6] introduce the importance and relevance of wavelet analysis and different disciplines. Gençay et al. [7–10] began to pay attention to the role of wavelet analysis in finance. Using the wavelet multiscale method to analyze foreign exchange volatility has different fluctuation rules in different periods, and the correlation between them is more obvious in low frequency. At the same time, a new asset pricing model based on the wavelet multiscale method is proposed, and the results show that the effect is obvious in the medium and long term. Nikkinen et al. [11] also proposed that the expected exchange rate has a different lead-lag relationship in the different frequency domains. Aguiar-Conraria et al. [12, 13] used cross-wavelet to study policy and macroeconomy for the first time and pointed out that there are significant differences in macroeconomy at different frequencies. And in the analysis of the linkage relationship between oil and macroeconomy, it is concluded that the causal relationship between the two has time-varying characteristics. Vacha and Barunik [14] revealed the correlation between energy commodity markets in the time domain and frequency domain. Tiwari et al. [15] studied the dynamic relationship between oil prices and Indian currency and concluded that there is a causal relationship between them in the long run. Yang et al. [16, 17] studied the linkage between foreign exchange markets and found that they were significantly linked to each other during the crisis. It is also found that the linkage relationship between oil price and exchange rate market is time-varying. In addition, the application of the wavelet analysis method in stock market research also began to develop. Rua and Nunes [18] used the wavelet method to analyze the linkage relationship between international stock markets from the perspective of time domain and frequency domain. Aloui and Hkiri [19] and Gallegati [20] use wavelet analysis to obtain the spillover effects of crisis events on the stock market. When Gherghina and Simionescu [21] studied the spillover relationship between the stock market and COVID-19, it was found that most stock markets showed the same cycle effect. Asafo-Adjei et al. [22] use wavelet coherence to analyze the dynamic impact of African economic policy uncertainty on eight African countries. The study found that most of the global EPU and African markets move together and concentrate for a long time, but short-term investment in African stocks is not easily affected by global economic policy uncertainty. Using continuous and discrete wavelet tools, Li et al. [23] found that the interaction of US economic policy uncertainty on Chinese and Indian stock markets is not significant in the short term, but gradually significant in the long term.

To further study the spillover effect between them and determine the spillover direction and spillover degree, Diebold and Yilmaz [24, 25] improved the variance decomposition model and redefined the spillover degree between sequences. However, the defect of this model is that it cannot describe the frequency domain characteristics of spillovers. To make it clear whether high-frequency spillover or low-frequency spillover is dominant in spillovers, Chen et al. [26] found that there are differences between short-term spillover and long-term spillover between the stock market and economic policy uncertainty. It can be seen that, with the continuous widening of the research perspective, many scholars study the spillover effect from the perspective of the frequency domain. Barunik et al. [27, 28] based on the DY spillover index [24], defined that the frequency domain is divided into short term, medium term, and long term, and the time-frequency dynamic connectivity between sequences is defined. It is found that the high-frequency spillover effect is significant. Naeem et al. [29] used the above research methods and found that the correlation between the energy market and oil is affected by crisis events, and the correlation is significantly increased, and the short-term effect is more obvious. Liu and Hamori [30] studied the relationship between energy stocks and investor sentiment based on the TVP-VAR method and found that the connectivity between energy stocks and investor sentiment increased during market turmoil. The results show that crude oil plays a leading role in the relationship between the two. Le et al. [31] studied the spillover effects between financial technology, bonds, and cryptocurrencies and found that the short-term volatility is more intense, so the holding risk is greater. Wang et al. [32] found that the linkage relationship between hedging and stock index changes with the timetable, and there is a difference between short-term and long-term hedging effects. Based on the frequency domain spillover, Zhang and Hamori [33] found that return

spillover is mainly short-term dominant, while volatility spillover is mainly long-term dominant, and the impact of COVID-19 on the market is greater than the financial crisis. Zhu et al. [34] found that there are obvious differences between the economic policy uncertainty and the dependence of the stock market in the time domain and frequency domain.

To sum up, few studies at home and abroad focus on analyzing the spillover effects of international EPU on China's Shanghai and Hong Kong stock market from the perspective of time domain and frequency domain. In this paper, the time-domain and frequency-domain frameworks are constructed by using wavelet coherence analysis and the work of Barunik and Křehlík [27]. The time domain is divided into the low, medium, and high frequencies to capture the spillover effects of international EPU on China's stock market and to analyze the time-varying spillover differences between the mainland stock market and the offshore stock market.

3. Materials and Methods

In order to achieve the above research purpose, this paper chooses wavelet coherence analysis and time-frequency-domain spillover index model. In this section, the principles and steps of each method are mainly introduced, in which wavelet coherence analysis can better deal with nonstationary time series and analyze the relationship between them in different time ranges, which is more in line with the data requirements of this paper. The lead-lag relationship between different research objects can be determined by using the spectrum diagram of wavelet coherence analysis, which provides the feasibility for the study of spillover index. In addition, the spillover index is further used to determine the coherent structure obtained by wavelet coherence. In the study of dy spillover index, the generalized prediction error variance decomposition matrix is selected instead of choresky variance decomposition, and the H-step prediction error variance of fluctuation is divided into the part of the impact of the variable itself and the part of the impact caused by the impact of other variables. At the same time, the frequency-domain spillover index is based on the generalized spectrum to study the lasting effects of spillover effects from low, medium, and high frequency. The above research methods all adopt more rigorous calculation steps.

3.1. Wavelet Coherence Model

3.1.1. Continuous Wavelet Definition. Compared with the traditional Fourier method, the wave coherence analysis can analyze the relevance and guiding status of the research object from the perspectives of time domain and frequency domain. First of all, the continuous wavelet transformation (CWT) transforms a function into a continuous wavelet basis function, which mainly depends on two parameters s and T, and then, the function is expanded to obtain the continuous wavelet transformation function:

$$W_{x,\psi}(\tau, s) = \langle x(t), \psi^*_{\tau,s}(t)\rangle = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)\mathrm{d}t, \tag{1}$$

where s and t represent scale factor and location factor, respectively. s represents the length of the wavelet and t represents the central position of the wavelet. * denotes complex conjugation. $\psi_{\tau,s}(t)$ represents the continuous wavelet basis function generated by the wavelet basis function $\psi(t)$ transform, which depends on two parameters.

3.1.2. Cross Wavelet Definition. Wavelet analysis can mainly carry out multidimensional analysis of a single research object, but in order to study the correlation degree of two-time series from the perspective of time domain and frequency domain, it is necessary to use cross-wavelet analysis.

Let the continuous wavelet transformation of two-time series $x = \{x_n\}$ and $y = \{y_n\}$ be W_x and W_y, respectively, and the specific expression of the cross-wavelet analysis between them is as follows:

$$W_{xy,\psi(\tau,s)} = W_{x,\psi(\tau,s)}W^*_{y,\psi(\tau,s)}, \tag{2}$$

where * denotes complex conjugation.

The specific expression of the cross-wavelet spectrum of the two-time series is as follows:

$$\left|W^{xy}\right| = \left|W^x W^{y^*}\right|. \tag{3}$$

Among them, the higher the value of $|W^{xy}|$ indicates that the two-time series have the same high-energy region, indicating that the coherence between the two is greater.

The wavelet correlation of two time series is in the form of the following formula:

$$R_{xy} = \frac{\left|S\left(W_{xy}\right)\right|^2}{\left|S\left(\left|W_x\right|^2\right)S\left(\left|W_y\right|^2\right)\right|}, \tag{4}$$

where S represents a smooth operator and conforms to

$$S(W) = S_{\text{scale}}\left(S_{\text{time}}\left(W_n(s)\right)\right). \tag{5}$$

Among them, S_{scale} and S_{time} are both Morlet wavelet operators, the former represents the scale axis smoothing, and the latter represents the time axis smoothing. The correlation degree of wavelet coherence ranges from 0 to 1, and its value indicates strong or weak correlation.

3.2. Spillover Model. First of all, this paper uses the 5-minute high-frequency closing price to calculate the daily volatility and then calculates the monthly volatility, such as formulae (6) and (7):

$$r_{j,d} = \ln\left(p_{d,j}\right) - \ln\left(p_{d,j-1}\right), \tag{6}$$

$$RV_m = \frac{1}{mn}\sum_{j=1}^{m}\sum_{i=1}^{n} r^2_{j,d}, \tag{7}$$

where m is the number of trading days in a month, n is the measured number of days, $r_{j,d}$ represents the daily rate of return of the stock markets, and $p_{d,j}$ represents the price of a stock index with a trading date of d and a trading cycle of j.

Diebold and Yilmaz [25] use the generalized prediction error variance decomposition instead of the traditional variance decomposition to divide the H-step prediction error variance of volatility into the part of the impact of the variable itself and the impact of other variables, that is, the volatility spillover from the variable j to the variable i:

$$\omega_{ij}^{H} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'\Psi_h\sum_{\varepsilon}e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i'\Psi_h\sum_{\varepsilon}\Psi_h'e_i\right)}. \tag{8}$$

Among them, $i, j = 1, 2, \ldots, N$. Σ_ε is the covariance matrix of the error term ε_t. σ_{jj} is the standard deviation of the error term of the j equation. e_i and e_j are selection vectors, where the i_{th} and j_{th} elements are 1, and the rest are 0.

The overall spillover effect formula is

$$S^H = 100 \times \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\omega}_{ij}^{H}}{\sum_{i,j=1}^{N}\widetilde{\omega}_{ij}^{H}} = 100 \times \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\omega}_{ij}^{H}. \tag{9}$$

Furthermore, Barunik and Křehlík [27] measure connectivity based on the frequency response to shocks to study the lasting effects of spillover effects from low, medium, and high frequencies. The formula is as follows:

$$\Psi\left(e^{-iw}\right) = \sum_{h} e^{-iwh}\Psi_h, \tag{10}$$

where Ψ_h is a $(N * N)$ matrix of moving average coefficients at lag h defined above. $\Psi(e^{-iw})$ can be obtained as a Fourier transform of the coefficients Ψ_h. Therefore, a generalized causal spectrum in frequency $w \in (-\pi, \pi)$ is defined as

$$(f(w))_{j,k} = \frac{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-iw}\right)\Sigma\right)_{j,k}\right|^2}{\Psi\left(e^{-iw}\right)\Sigma\Psi'\left(e^{+iw}\right)_{j,j}}, \tag{11}$$

where $\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$ is shock response Ψ_h Fourier transformation and $(f(w))_{j,k}$ said on the frequency of w, the first j element for the first k elements caused by the impact of the ratio of the spectrum. The weighting method is defined as

$$\Gamma_j(w) = \frac{\Psi\left(e^{-iw}\right)\Sigma\Psi'\left(e^{+iw}\right)_{j,j}}{(1/2\pi)\int_{-\pi}^{\pi}\left(\Psi\left(e^{-i\lambda}\right)\Sigma\Psi'\left(e^{+i\lambda}\right)\right)_{j,j}\mathrm{d}\lambda}, \tag{12}$$

where $\Gamma_j(w)$ is the power of the jth element at a given frequency w. The sum of its frequencies is the constant 2π, and the spectral expression of the variance decomposition from J to K is established (13):

$$(\theta_\infty)_{j,k} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_j(w)(f(w))_{j,k}\mathrm{d}w. \tag{13}$$

The connectivity measure on the fixed frequency band is as follows:

$$\left(\widetilde{\theta}_d\right)_{j,k} = \frac{(\theta_d)_{j,k}}{\sum_k(\theta_\infty)_{j,k}}. \tag{14}$$

Among them, d coincidence formula $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$.

The definition of internal connectivity of frequency band d is as follows:

$$C_d^w = 100 \cdot \left(1 - \frac{\mathrm{Tr}\left\{\widetilde{\theta}_d\right\}}{\Sigma\widetilde{\theta}_d}\right). \tag{15}$$

The definition of frequency connectivity of frequency band d is shown as

$$C_d^F = 100 \cdot \left(\frac{\Sigma\widetilde{\theta}_d}{\Sigma\widetilde{\theta}_\infty} - \frac{\mathrm{Tr}\left\{\widetilde{\theta}_d\right\}}{\Sigma\widetilde{\theta}_\infty}\right) = C_d^w \cdot \frac{\Sigma\widetilde{\theta}_d}{\Sigma\widetilde{\theta}_\infty}, \tag{16}$$

where $\mathrm{Tr}\{\cdot\}$ represents the track operators and $\Sigma\widetilde{\theta}_d$ said all elements $\widetilde{\theta}_d$ of the sum matrix.

4. Results and Discussion

4.1. Data and Descriptive Statistics. This paper studies the time-frequency volatility spillover of international EPU on China's stock market, in order to reflect the international EPU more comprehensively, select China, the United States, Australia, and the United Kingdom, and use the monthly EPU index of these countries and regions. Among them, China chooses China's EPU and Hong Kong's EPU index. At the same time, the 5-minute high-frequency realized volatility of the SSEC and HSI is selected to represent the Shanghai and Hong Kong stock market, respectively. The data sample spans from January 2000 to February 2021, excluding a total of 254 missing values. This paper uses the monthly EPU index compiled by Baker et al. [1], derived from https://www.policyuncertainty.com, and 5-minute high-frequency data are from https://www.realized.Oxford-man.ox.ac.uk/.

For example, Tables 1 and 2 show the descriptive statistical data and unit root test of EPU index and stock index, respectively. The results show that all variables reject the original hypothesis, indicating that each time series is a stationary series.

In terms of average, the average value of the EPU index of the United States is the largest (4.814606), while that of Australia is the lowest (4.51604). From the perspective of standard deviation, the standard deviation of China's EPU is the largest (0.735862), while that of the United States is the smallest (0.431434), indicating that China's EPU fluctuates greatly. Similarly, it can be concluded from Table 2 that the volatility of the Shanghai Composite Index is greater than that of the Hang Seng Index. From the ADF test, it can be seen that each time series does not obey the normal distribution, and there is a significant ARCH effect and sequence correlation.

At the same time, from the kurtosis of the EPU index, we can see that the EPU is becoming more and more significant, indicating that it is more and more affected by economic

Table 1: Descriptive statistics and unit root test of EPU index of various countries.

	China	HK	US	UK	Australia
Mean	4.570477	4.742472	4.814606	4.707553	4.51604
Median	4.583349	4.776579	4.763996	4.779984	4.505456
Maximum	6.495006	6.052941	6.222504	6.32476	5.820213
Minimum	2.313657	3.135981	3.801823	3.17955	3.24501
Std. dev.	0.735862	0.556914	0.431434	0.538723	0.548169
Skewness	0.268719	−0.271778	0.381081	−0.16292	0.023068
Kurtosis	2.885763	2.750439	3.245789	2.822462	2.570653
Jarque–Bera	3.194999	3.786023	6.787128	1.457285	1.973446
ADF	−3.995189***	−3.995492***	−3.994744***	−6.143366***	−4.937559***

Note: ** indicates significance at 5% level and ** indicates significance at 1% level.

Table 2: Descriptive statistics and unit root test of SSEC and HSI.

	SSEC	HSI
Mean	−9.191876	−6.556836
Median	−9.281615	−6.687046
Maximum	−6.657218	−3.615086
Minimum	−10.97081	−7.724878
Std. dev.	0.913208	0.72501
Skewness	0.433321	0.941521
Kurtosis	2.629457	3.868389
Jarque–Bera	9.401923	45.50775
ADF	−5.547368***	−4.352010***

Note: ** indicates significance at 5% level and ** indicates significance at 1% level.

events. The main reasons are the financial crisis in 2015, the impact of China's entry into the new economic normal in 2008–2017, Brexit, and the intensification of trade conflicts between China and the United States in 2018.

4.2. Wavelet Coherence Analysis

4.2.1. Continuous Wavelet Analysis. Wavelet coherence analysis is widely used to measure the time-frequency relationship of different financial variables. This paper uses a wavelet to analyze the correlation between EPU and the stock market. In the analysis of time series, in order to obtain smooth and continuous wavelet amplitude, the non-orthogonal wavelet function is more functional, and to analyze the time-frequency spillover effects of different research objects, complex-valued wavelets are selected, while Morlet wavelets are not only nonorthogonal but also exponentially complex-valued wavelets with Gaussian regulation. To analyze the fluctuation law of a single time series, the continuous wavelet transformation of each index is calculated by using Morlet wavelet as the generating function. The results are shown in Figures 1–7. The color on the right side of the picture represents the degree of correlation, from blue to yellow, indicating that the variance of the time series is gradually increasing, which shows that the greater the volatility. The horizontal axis represents time, while the vertical axis represents different frequency periods. The black line is the influence cone curve, for the area far away from the cone curve, because the influence of the boundary effect should be taken into account, so the significance of the analysis reference is small.

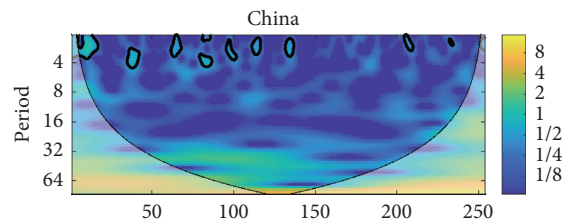

Figure 1: Uncertainty of China's economic policy, a continuous wavelet transformation power spectrum figure.

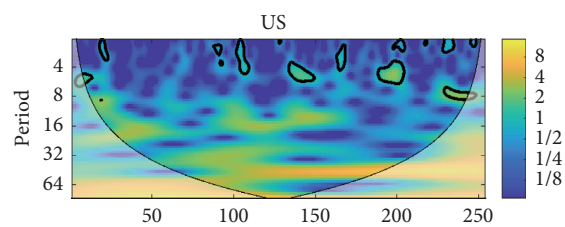

Figure 2: Uncertainty of US economic policy, a continuous wavelet transformation power spectrum.

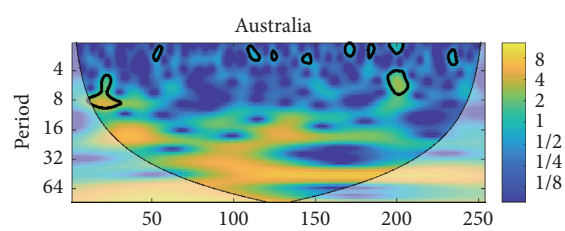

Figure 3: Uncertainty of Australia economic policy, a continuous wavelet transformation power spectrum.

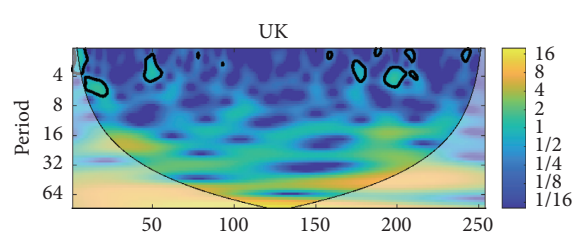

Figure 4: Uncertainty of UK economic policy, a continuous wavelet transformation power spectrum.

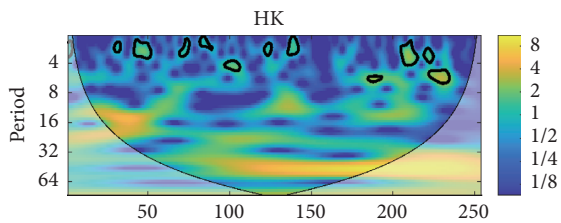

Figure 5: Uncertainty of HK economic policy, a continuous wavelet transformation power spectrum.

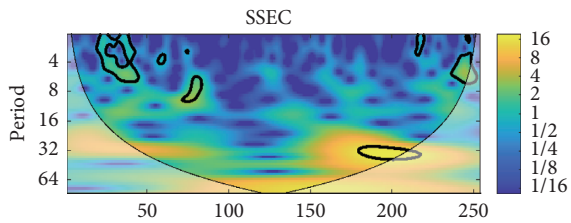

Figure 6: Shanghai composite index, a continuous wavelet transformation power spectrum.

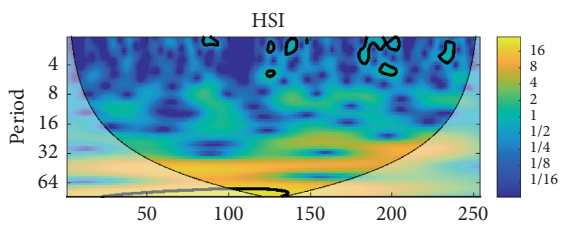

Figure 7: Hong Kong HSI, a continuous wavelet transformation power spectrum.

From Figures 1 to 5, we can see that the continuous wavelet analysis spectrum of EPU in various countries shows that China's EPU index is a low-energy region represented by blue, indicating that its fluctuation is weak. On the contrary, there are two obvious yellow high-energy regions in Hong Kong's EPU index, indicating that the time series of this index fluctuates strongly. Among them, the first region is from 2000 to 2003 and the second region is from 2008 to 2020, which is mainly affected by the return of Hong Kong in 1997 and the financial crisis in 2008. In addition, there are also some high-energy regions in the United States and the United Kingdom, in which the economic policy of the United States fluctuated greatly from 2007 to 2011 due to the subprime mortgage crisis in the United States, while the United Kingdom was affected by Brexit and fluctuated sharply from 2012 to 2019.

From Figures 6 and 7, we can see, from the continuous wavelet analysis spectrum of EPU of various countries, that it was influenced by the macroeconomic policy of the central bank raising the benchmark deposit interest rate six times in 2007. The rise and fall of the SSEC have an obvious fluctuation impact. At the same time, due to the impact of the subprime mortgage crisis, China's stock market fell sharply and fluctuated violently. In particular, the rise of Hong Kong's Hang Seng index was mainly due to the return of Hong Kong in 1997 and the global Internet revolution in 2000. Second, after 2008, the global economy gradually recovered, the stock market showed a technical rebound, the HSI was in an upward state, and the overall fluctuation range was obvious.

4.2.2. Cross Wavelet Analysis. Based on the above research, this paper analyzes the correlation degree and lead-lag relationship between them through the wavelet coherent cross-spectrum analysis of different time series. The results are shown in Figures 8–17. Figures 8–12 shows the cross-wavelet cross-spectral analysis of national EPU and SSEC, and Figures 13–17 shows the cross-wavelet cross-spectral analysis of national EPU and HSI. The color on the right side of the picture represents the degree of correlation between the two, ranging from blue to yellow, indicating that the degree of coherence is gradually increasing. In this paper, 0–3 months are defined as short term (high frequency), 4–12 months are defined as medium term (intermediate frequency), and more than 12 months are defined as long term (low frequency). The arrow from left to right indicates that there is a positive correlation between the EPU index and the change of stock index and a negative correlation between them from left to right. The arrow pointing to the upper left or lower right indicates that the EPU is ahead of the stock market, while the arrow direction of the lower left or upper right indicates that the stock market is ahead of the EPU. In addition, the arrow direction is right, and maintaining the horizontal direction indicates that there is a two-way guiding relationship between EPU and the stock market.

As can be seen from the chart, there are obvious differences between the EPU and the dependence of the stock market in time domain and frequency domain, and the dependence between them mainly occupies a medium-and long-term dominant position in the frequency domain. For the Shanghai stock market, the EPU of Hong Kong is the strongest, followed by the EPU of the United States and Australia. However, the overall EPU of China and the United Kingdom have relatively low dependence on the Shanghai Composite Index. This is mainly due to the fact that the mainland stock market has a relatively rich investment portfolio and a relatively large proportion of foreign investment. As an important offshore financial market in China, the fluctuations of its economic policies will have a greater impact on the mainland stock market. The two maintain a relatively high degree of consistency. As the most developed country in the world as well as China's trade exporter and importer, the implementation of its economic policy will have a certain impact on the global economy. At the same time, for the Hong Kong stock market, the EPU of Hong Kong and the United Kingdom has the strongest dependence on the Hang Seng Index, while the dependence on the EPU of China, the United States, and Australia is relatively weak. This is because the Hong Kong stock market, as a diversified financial market, has a relatively large number of overseas investors and is vulnerable to changes in the policies of overseas countries.

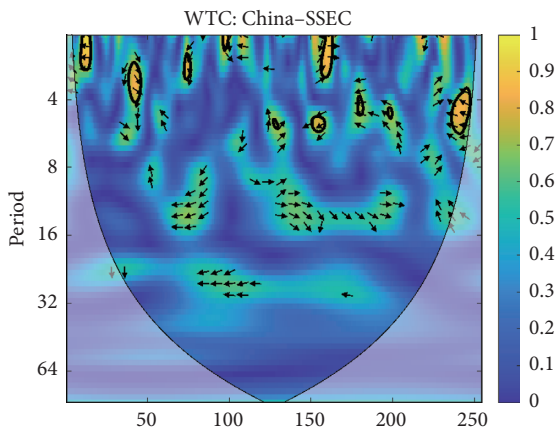

Figure 8: Uncertainty of China's economic policy and cross-wavelet cross-spectrum of Shanghai composite index.

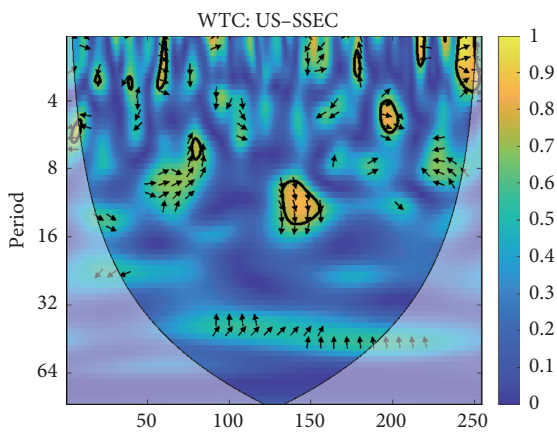

Figure 9: Uncertainty of US economic policy and cross-wavelet cross-spectrum of Shanghai composite index.

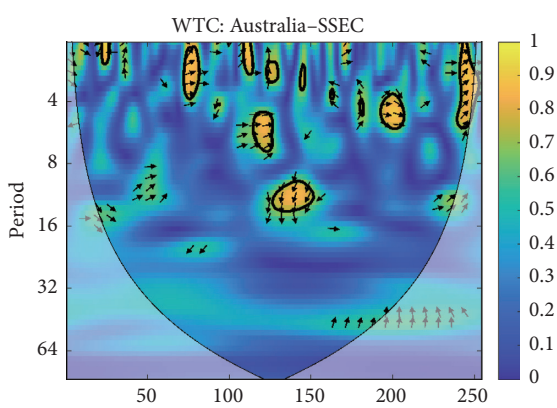

Figure 10: Uncertainty of Australia economic policy and cross-wavelet cross-spectrum of Shanghai composite index.

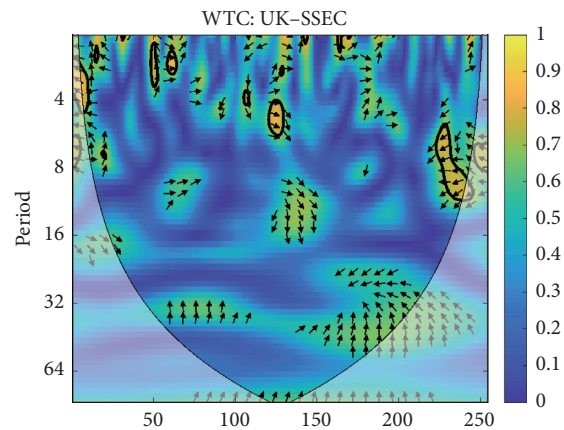

Figure 11: Uncertainty of UK economic policy and cross-wavelet cross-spectrum of Shanghai composite index.

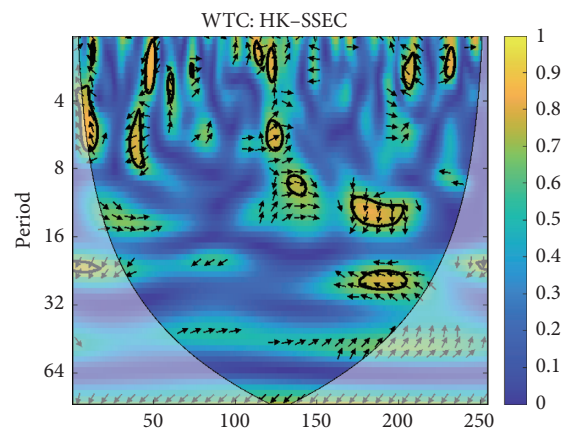

Figure 12: Uncertainty of HK economic policy and cross-wavelet cross-spectrum of Shanghai composite index.

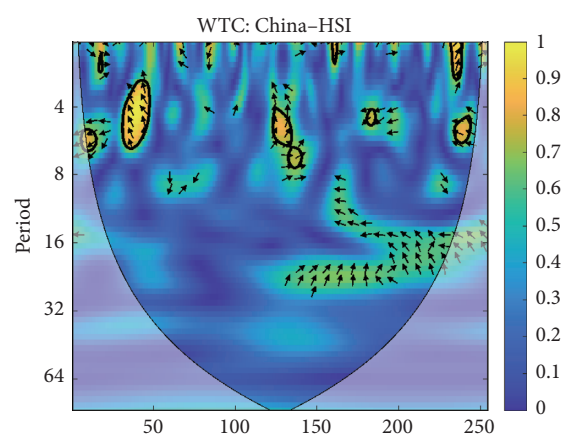

Figure 13: Uncertainty of China's economic policy and cross-wavelet cross-spectrum of HIS.

In addition, from the perspective of time domain, due to the influence of the 2008 financial crisis, the dependence of US EPU on the Shanghai stock market and Shenzhen stock market increased significantly after the financial crisis. Especially, in the important areas of its impact on the Hang Seng Index, there are more phase arrows pointing to the upper right and lower left, indicating that the uncertainty of economic policy is ahead of the Hang Seng Index. On the

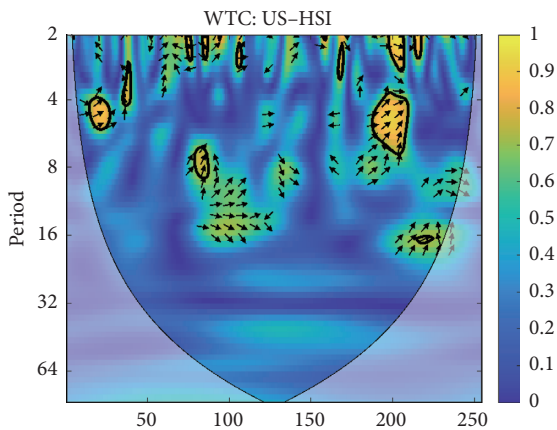

Figure 14: Uncertainty of US economic policy and cross-wavelet cross-spectrum of HSI.

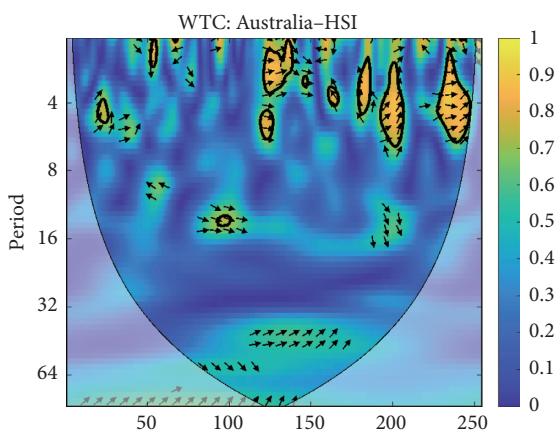

Figure 15: Uncertainty of Australia economic policy and cross-wavelet cross-spectrum of HSI.

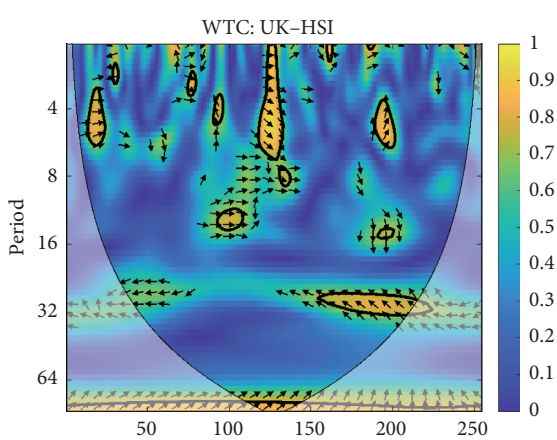

Figure 16: Uncertainty of UK economic policy and cross-wavelet cross-spectrum of HSI.

contrary, the EPU of Hong Kong and the arrows of the Shanghai Composite Index and Hang Seng Index point to the right and horizontal, indicating that the EPU and the Shanghai and Hong Kong stock markets are in a mutually

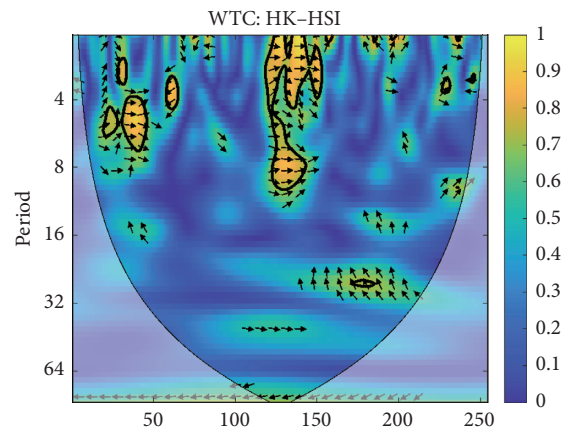

Figure 17: Uncertainty of HK economic policy and cross-wavelet cross-spectrum of HSI.

guiding relationship during the financial crisis. As a result of the Sino-US trade war in 2018, the Shanghai Composite Index and the EPU of China, the United States, the United Kingdom, and Hong Kong are the upper right-hand corner, indicating that EPU is ahead of the stock market. However, after 2018, the phase arrow between the Hang Seng Index and EPU in China, the UK, and Hong Kong points to the upper left corner, indicating that the stock market is leading EPU. Therefore, based on the results of wavelet coherence analysis, it can be concluded that Shanghai and Shenzhen stock markets are highly dependent on the EPU of Hong Kong and the United Kingdom. And the dependence between the two has obvious time-varying characteristics and medium-and long-term dominant frequency-domain characteristics.

4.3. Analysis of Spillover Effect in Time Domain and Frequency Domain

4.3.1. Static Spillover Effect in Time Domain and Frequency Domain. In order to further measure the spillover direction and degree of EPU of each country or region on the Shanghai and Hong Kong stock market, the first step is to use the Diebold–Yilmaz method to calculate the time-domain spillover index of five countries and regions for SSEC and HSI, respectively. The results are shown in Tables 3 and 4. It can be concluded that, first of all, the overall spillover effect of the EPU of the five countries on the Shanghai Composite Index is as high as 35.57%, but it is still less than its overall spillover effect on the Hang Seng Index, indicating that there is a strong correlation between the economic uncertainty of these countries and regions, that is, the degree of economic risk contagion between countries may be greater. Among them, the correlation with the Hong Kong stock market is greater than that with the Shanghai stock market mainly due to the fact that Hong Kong's offshore market is vulnerable to foreign investment. Second, for the Shanghai stock market, China's EPU has the greatest impact on its spillover degree (1.79%), followed by US EPU (1.35%), and UK EPU (1.34%) has the least impact on it. As for the

Hong Kong stock market, the degree of spillover caused by EPU in the United States (5.73%), Australia (4.76%), and the United Kingdom (3.72%) is far greater than that in Hong Kong and China; the main reason is that domestic consumption is relatively stable, while the United States is China's main trading partner and has a large demand for imports of Chinese products. In recent years, under the influence of Sino-US trade disputes, the greater uncertainty of US economic policy has posed a great challenge to China's import and export trade, resulting in a relatively large spillover relationship between US economic policy and China's consumer industry. Finally, in the spillover relationship between the two, for the Shanghai stock market, different economic policy uncertainties dominated the spillover of the SSEC, with a FROM of 0.9% greater than TO (0.61%), while for the Hong Kong stock market, the HSI dominated the spillover of different economic policy uncertainties, with a FROM of 2.74% less than TO (4.11%).

Because the EPU and the time-domain spillover analysis of the stock market cannot capture the spillover effects of EPU in different frequencies, but for policymakers and market participants, the persistence and contagion of systemic risk are very important. Therefore, the second step of this paper uses Baruink–Krehlik's method to construct a frequency-domain framework to explore EPU and frequency-domain spillover effects of the stock market in short term (0–3 months), medium term (4–12 months), and long term (more than 12 months). The results are shown in Tables 5–10.

On the one hand, the EPU of different countries and regions dominates the long-term (low frequency) spillover effects of Shanghai and Hong Kong stock markets, that is, the degree of spillover between them increases with time. This result is consistent with the findings of Baruink, which found that low frequency plays a dominant role in estimating the connectivity of short-term, medium-term, and long-term financial cycles. Among them, the total spillover rate of short-term (0–3 months) EPU to Shanghai stock market is 0.12%, medium term (4–12 months) is 0.1%, long term (more than 12 months) is 0.67%, and the total spillover rate of short-term (0–3 months) EPU to Hong Kong stock market is 0.58%. The medium term (4–12 months) and long term (more than 12 months) are 0.35% and 1.81%, respectively. It can be seen that the spillover of EPU on the Shanghai stock market is less than that on the Hong Kong stock market at different frequencies. It shows that different economic policy uncertainties are more related to the Hong Kong stock market, which is consistent with the analysis of time-domain results.

On the other hand, the spillover relationship between EPU and the stock market has time-varying characteristics. For the Shanghai stock market, the degree of spillover of EPU is larger in the United States (0.21%, 0.22%) and Australia (0.29%, 0.22%) in the short- and medium-term frequency, while in the long-term frequency. China's EPU spillover to it is 1.52%. For the Hong Kong stock market, the EPU dominates the spillover of the Hang Seng Index in the short-term frequency, that is, the HSI is the main recipient, while with the increase of the time span, in the medium and long term, the spillover of the HSI to the EPU is dominant, that is, the HSI is the main sender.

Table 3: Uncertainty of international economic policy and static time-domain spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM
SSEC	94.62	1.79	0.5	1.35	0.39	1.34	0.9
China	0.45	61.93	6.03	9.9	12.57	9.12	6.35
HK	1.71	10.96	70.15	4.53	4.24	8.41	4.97
US	0.45	8.52	3.54	47.43	15.51	24.54	8.76
UK	0.2	11.07	4.25	12.89	53.94	17.65	7.68
Australia	0.86	2.87	4.25	16.26	17.24	58.52	6.91
TO	0.61	5.87	3.09	7.49	8.33	10.18	35.57

Table 4: International EPU and static time-domain spillover index of HSI.

	HSI	China	HK	US	UK	Australia	FROM
HSI	83.55	0.72	1.52	5.73	3.72	4.76	2.74
China	1.91	59.52	6.06	9.67	13.15	9.69	6.75
HK	2.34	10.96	69.01	4.02	4.27	9.39	5.16
US	7.11	8.82	3.24	43.83	15.2	21.79	9.36
UK	4.36	11.22	4.28	11.87	51.12	17.15	8.15
Australia	8.93	3.49	4.19	14.92	16.75	51.72	8.05
TO	4.11	5.87	3.22	7.7	8.85	10.46	40.21

4.3.2. Dynamic Frequency-Domain Spillover Effect. As the frequency reflected by static spillover effects is fixed, it is impossible to analyze the impact of economic events at different time points on EPU and stock market spillover effects from a dynamic perspective. These crisis events have a certain impact on the direction and degree of spillover between the two. Therefore, in order to further analyze the risk spillover combined with economic events, this paper carries on the dynamic frequency-domain spillover analysis by setting the rolling window to 24 and the prediction range to 10 in advance. The result is shown in Figures 18–25. Among them, Figures 18 and 19 show the dynamic frequency-domain spillover of the SSEC, HSI, and EPU, which shows that there are obvious time-varying characteristics in the dynamic correlation between the two. The impact of the global financial crisis from 2008 to 2010 continues to ferment, and the scope extends from the United States to China and other countries and from the fictitious economy to the real economy, which leads to consumer market panic, which makes the spillover of the EPU shock to the stock market risk even greater. The debt crisis of 2010–2012 and Brexit in 2016 brought all kinds of uncertainty, the EPU of various countries was affected to a certain extent, and the degree of spillover has also greatly increased. The trade war between China and the United States in 2018, the Brexit incident in 2019, and the riots in Hong Kong, as well as the COVID-19 epidemic in 2020 and the correlation between EPU and the stock market, increased significantly; especially during the financial crisis, the total dynamic frequency-domain spillover between the two increased sharply mainly due to the continuous expansion and deepening of the global spread of

Table 5: Uncertainty of international economic policy and static short-term (0–3 months) spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
SSEC	14.47	0.15	0.03	0.21	0.06	0.29	0.12	0.75
China	0.13	9.2	0.09	0.09	0.03	0.15	0.08	0.5
HK	0.14	0.42	25.04	0.89	0.22	1.32	0.5	3.06
US	0.17	0.25	0.35	11.89	1.34	1.91	0.67	4.12
UK	0.01	0.1	0.07	1.12	9	1.22	0.42	2.59
Australia	0.18	0.05	0.68	2.19	1.67	12.34	0.8	4.9
TO_ABS	0.1	0.16	0.2	0.75	0.55	0.82	2.59	
TO_WTH	0.64	1	1.25	4.62	3.41	5.02		15.94

Table 6: International EPU and static medium-term (4–12 months) spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
SSEC	12.54	0.13	0.03	0.22	0.01	0.22	0.1	0.93
China	0.06	3.61	0.13	0.16	0.11	0.13	0.1	0.9
HK	0.14	0.37	14.14	0.56	0.13	1.21	0.4	3.67
US	0.11	0.08	0.26	7.62	1.15	2.51	0.68	6.24
UK	0.01	0.05	0.14	0.84	6.11	1.15	0.36	3.32
Australia	0.17	0.06	0.42	1.76	1.47	7.97	0.65	5.9
TO_ABS	0.08	0.12	0.16	0.59	0.48	0.87	2.3	
TO_WTH	0.75	1.05	1.48	5.38	4.36	7.95		20.97

Table 7: Uncertainty of international economic policy and static long-term (more than 12 months) spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
SSEC	67.62	1.52	0.44	0.93	0.32	0.83	0.67	0.92
China	0.26	49.11	5.81	9.65	12.43	8.83	6.16	8.47
HK	1.43	10.16	30.98	3.08	3.89	5.88	4.07	5.6
US	0.17	8.2	2.93	27.92	13.02	20.13	7.41	10.18
UK	0.18	10.92	4.05	10.93	38.83	15.27	6.89	9.47
Australia	0.51	2.75	3.15	12.31	14.1	38.21	5.47	7.51
TO_ABS	0.43	5.59	2.73	6.15	7.29	8.49	30.68	
TO_WTH	0.58	7.68	3.75	8.45	10.02	11.66		42.15

Table 8: Uncertainty of international economic policy and static short-term (0–3 months) spillover index of HSI.

	HSI	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
HSI	13	0.08	0.56	1.09	0.7	1.03	0.58	3.64
China	0.04	8.67	0.09	0.09	0.03	0.15	0.07	0.41
HK	0.85	0.36	24.61	0.95	0.22	1.45	0.64	4.03
US	0.71	0.23	0.3	10.33	1.16	1.61	0.67	4.23
UK	0.39	0.09	0.06	1.04	8.24	1.12	0.45	2.85
Australia	0.67	0.06	0.65	1.83	1.47	10.98	0.78	4.93
TO_ABS	0.44	0.14	0.28	0.83	0.6	0.89	3.18	
TO_WTH	2.8	0.86	1.76	5.25	3.78	5.65		20.1

the financial crisis. Reduced portfolio returns. In addition, China's economy has entered a new normal; as a result, EPU has a greater impact on the stock market risk. Secondly, it can be concluded that the dynamic frequency-domain spillover between EPU and the stock market is mainly dominated by long-term frequency, which is consistent with the results of the static spillover analysis above. Finally, comparing the Shanghai and the Hong Kong stock market, we can find that the spillover of EPU on the Hong Kong stock market is larger than that of the Shanghai stock market, which is also consistent with the results of static time-domain spillover analysis.

To reflect the EPU and the dynamic risk spillover direction of the stock market more directly, this paper reveals

Table 9: International EPU and static medium-term (4–12 months) spillover index of HSI.

	HSI	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
HSI	8.04	0.03	0.37	0.6	0.42	0.67	0.35	3.46
China	0.02	3.37	0.13	0.16	0.11	0.14	0.09	0.91
HK	0.59	0.36	13.99	0.6	0.15	1.44	0.52	5.17
US	0.57	0.07	0.2	6.77	1.01	2.1	0.66	6.5
UK	0.31	0.04	0.13	0.78	5.59	1.09	0.39	3.89
Australia	0.62	0.08	0.42	1.46	1.3	6.99	0.65	6.39
TO_ABS	0.35	0.1	0.21	0.6	0.5	0.91	2.66	
TO_WTH	3.48	0.95	2.07	5.92	4.92	8.97		26.31

Table 10: Uncertainty of international economic policy and static long-term (more than 12 months) spillover index of HSI.

	HSI	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
HSI	62.52	0.62	0.58	4.04	2.59	3.06	1.81	2.45
China	1.85	47.48	5.84	9.42	13.01	9.41	6.59	8.9
HK	0.9	10.24	30.42	2.47	3.91	6.5	4	5.41
US	5.83	8.51	2.74	26.73	13.03	18.08	8.03	10.85
UK	3.66	11.09	4.09	10.05	37.28	14.93	7.3	9.86
Australia	7.64	3.35	3.12	11.64	13.98	33.75	6.62	8.94
TO_ABS	3.31	5.64	2.73	6.27	7.75	8.66	34.36	
TO_WTH	4.47	7.61	3.68	8.47	10.47	11.7		46.4

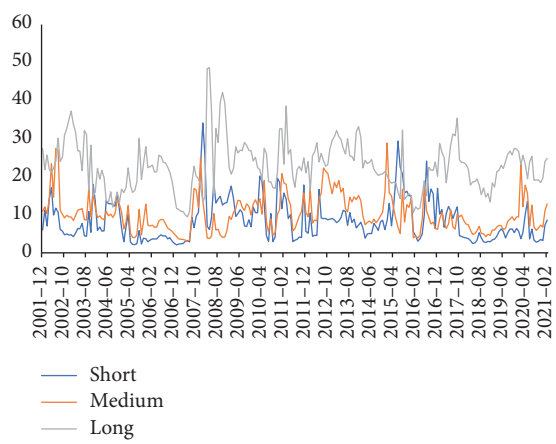

Figure 18: Dynamic total frequency connection between Shanghai composite index and EPU index.

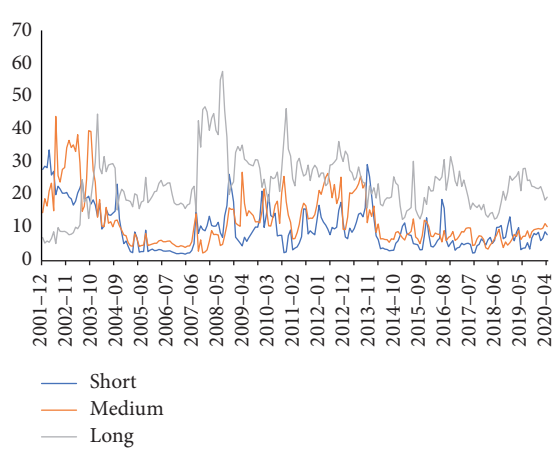

Figure 19: Dynamic total frequency connection between HSI and EPU index.

the role of the market in the risk spillover by calculating the dynamic risk spillover, which the "TO_ABS" spillover value minus the "FROM_ABS" spillover value is used to represent the net risk spillover, the positive value represents the market as the risk sender, and the negative value represents the market as the risk receiver. The result is shown in Figures 20–25. On the one hand, for the Shanghai stock market, the net spillover value of China's overall EPU is negative in the short-term and positive in the medium and long term, indicating that China's EPU is the receiver of risk spillover in the short term and the sender of risk spillover in the medium and long term. This is mainly due to the impact of the promotion of the internationalization of RMB in 2009 and the successful implementation of the G20 summit to promote a new international financial order. The international economic situation is showing a trend for the better. In addition, China's economy entered a new normal in 2014 and the development of the "Belt and Road Initiative" further deepened China's opening up to the outside world. Even under the influence of the COVID-19 epidemic in 2020, the net spillover effect is still positive, which indicates that China's economic policy plays a key guiding role in stabilizing the national economy and investor sentiment in the long-term development process. Hong Kong, the United States, the United Kingdom, and Australia are mainly recipients. For the Hong Kong stock market, the HSI as the main sender shows that the HSI dominates the spillover of EPU, which is consistent with the results of static analysis. On the contrary, under the influence of economic events such as the financial crisis, the Sino-US trade war, and Brexit, there are positive and reverse oscillations in the dynamic risk spillover. This shows that there is a two-way and asymmetric risk spillover between EPU and the stock market.

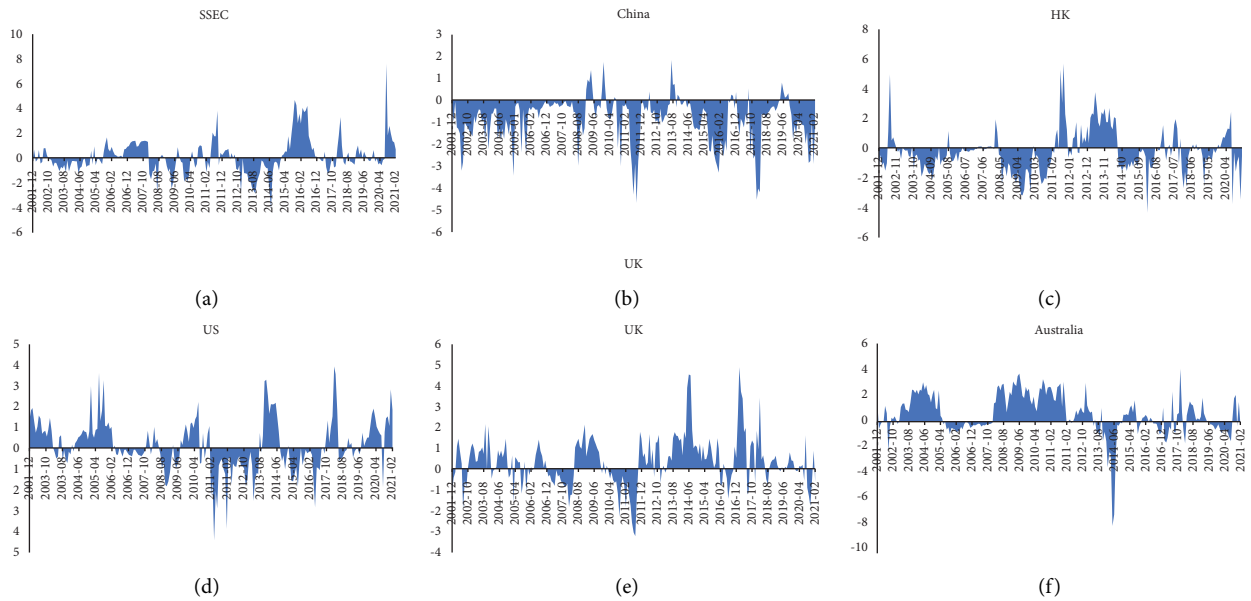

Figure 20: Short-term dynamic net spillover of Shanghai composite index and EPU.

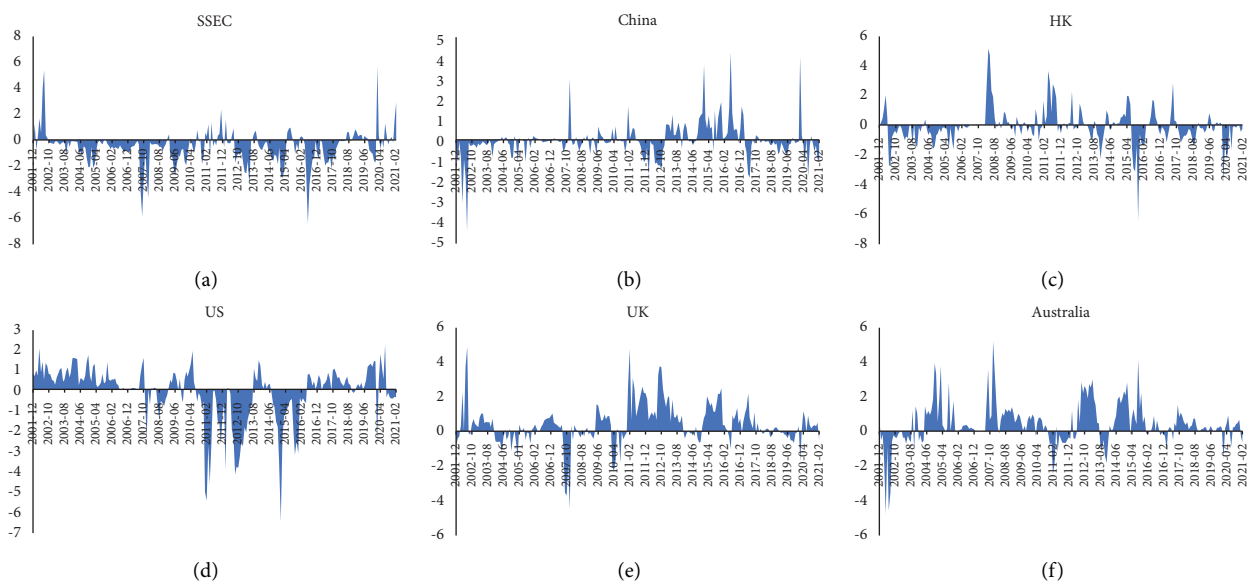

Figure 21: Medium-term dynamic net spillover of Shanghai composite index and EPU.

5. Robustness Test

5.1. Robustness Test Based on Window Value. In order to judge whether the empirical conclusions obtained under the selected model parameters are robust, this section selects different window periods to test the robustness. Because the data used in this paper are monthly data, the length of time series has some limitations, so this section selects the window period of 24 months and 36 months, respectively, for test and analysis. The overall spillover chart of the Hang Seng Index in the frequency-domain is shown in Figures 26 and 27. By comparison, it can be concluded that when the window period becomes larger, the change range of the dynamic spillover index becomes smaller and the whole is smoother, but the specific upward and downward trends are similar.

First of all, the overall spillover fluctuation of the Hang Seng Index in the frequency domain is obvious during the period from 2007 to 2010, indicating that the spillover effect between the two increases and occupies a dominant position for a long time due to the influence of domestic and foreign economic events. Secondly, under the condition that the window period is 30, the short-term and medium-term spillover effect is relatively smooth, and compared with the window period of 24 months, the change range is smaller, but the fluctuation trend tends to be consistent, and the two

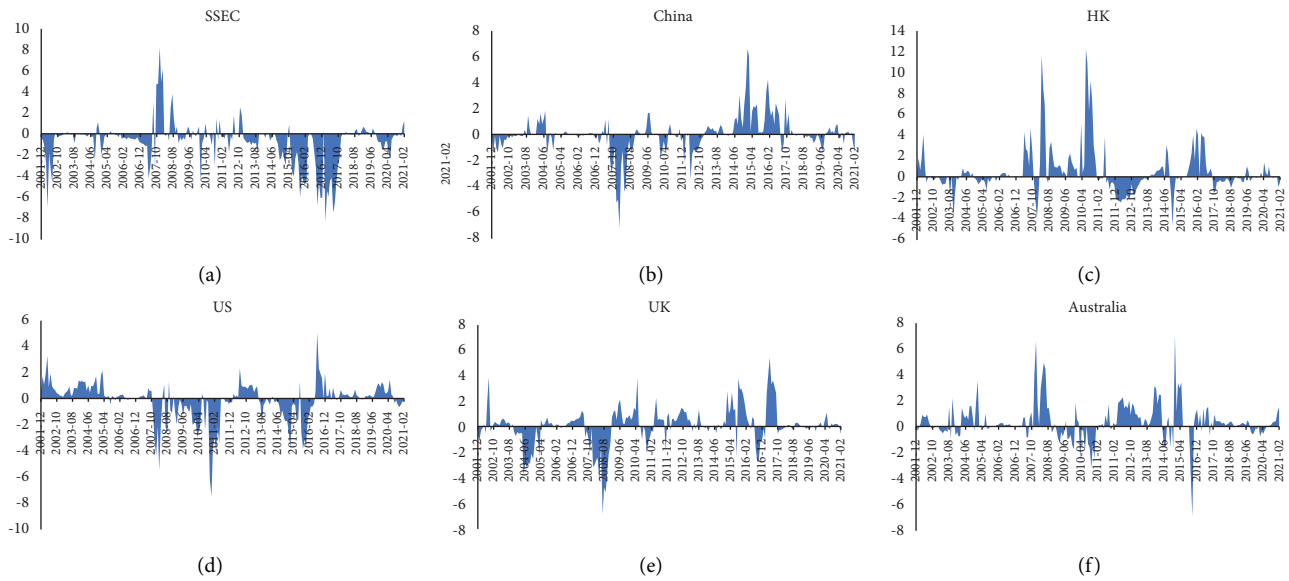

Figure 22: Long-term dynamic net spillover of Shanghai composite index and EPU.

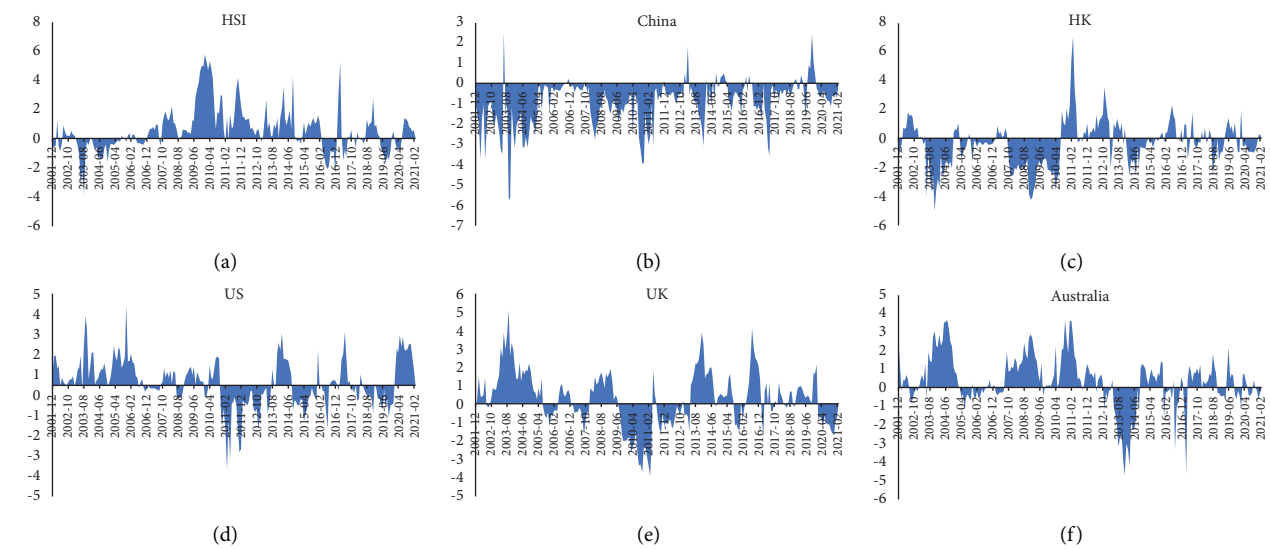

Figure 23: Short-term dynamic net spillover of HSI and EPU.

are similar in time. Generally speaking, although there are some deviations in the specific numerical calculation of the dynamic spillover index in different window periods, the conclusions are basically the same. Therefore, it can be considered that the empirical conclusion obtained under the condition of the model parameters of the selected 24-month window period is robust.

5.2. Robustness Test Based on the Lag-Order Value. In order to judge whether the lag order in the model has an impact on the empirical analysis results, this section selects the lag order to test the robustness of the frequency-domain spillover model. Because there are some limitations in the length of time series in this paper, this section chooses lag order 3 and lag order 2, respectively, for test and analysis. The international EPU with lag order 3 and the static frequency-domain spillover index of Shanghai Composite Index are shown in Tables 11–13.

Compared with the results of Tables 5–7, it can be concluded that although there are differences between the international economic and political uncertainty and the static spillover index of the SSEC, the overall conclusion remains the same. On the one hand, from Tables 11 to 13, it can be seen that the long-term (low frequency) spillover effects of EPU in different countries/regions are dominant from short-, medium-, and long-term static spillover tables. Among them, the total spillover rate of EPU for the Shanghai

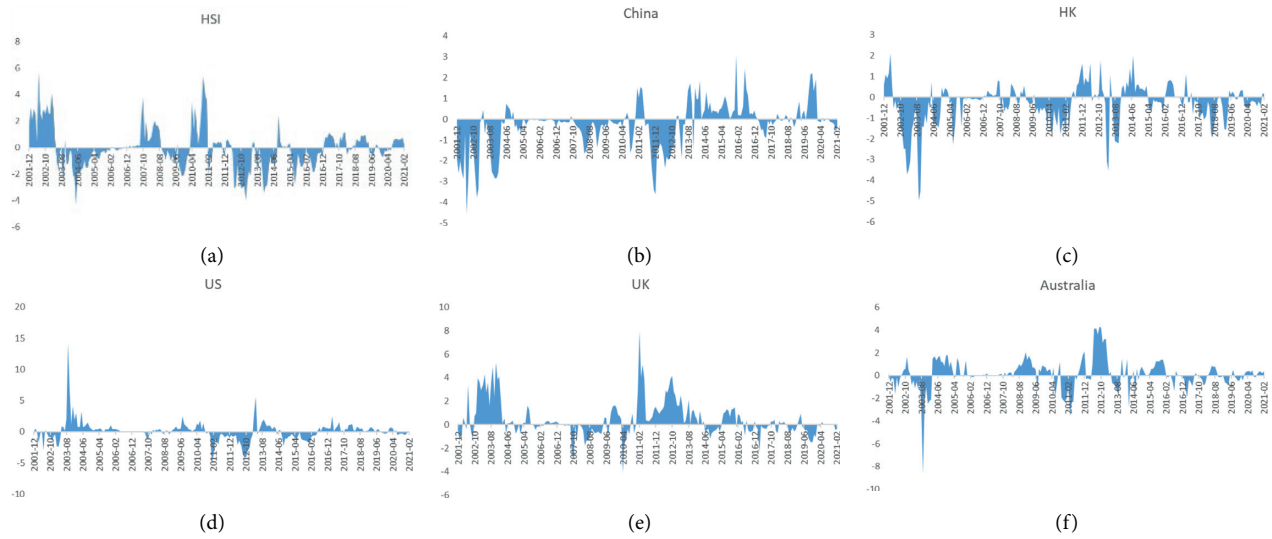

Figure 24: Medium-term dynamic net spillover of HSI and EPU.

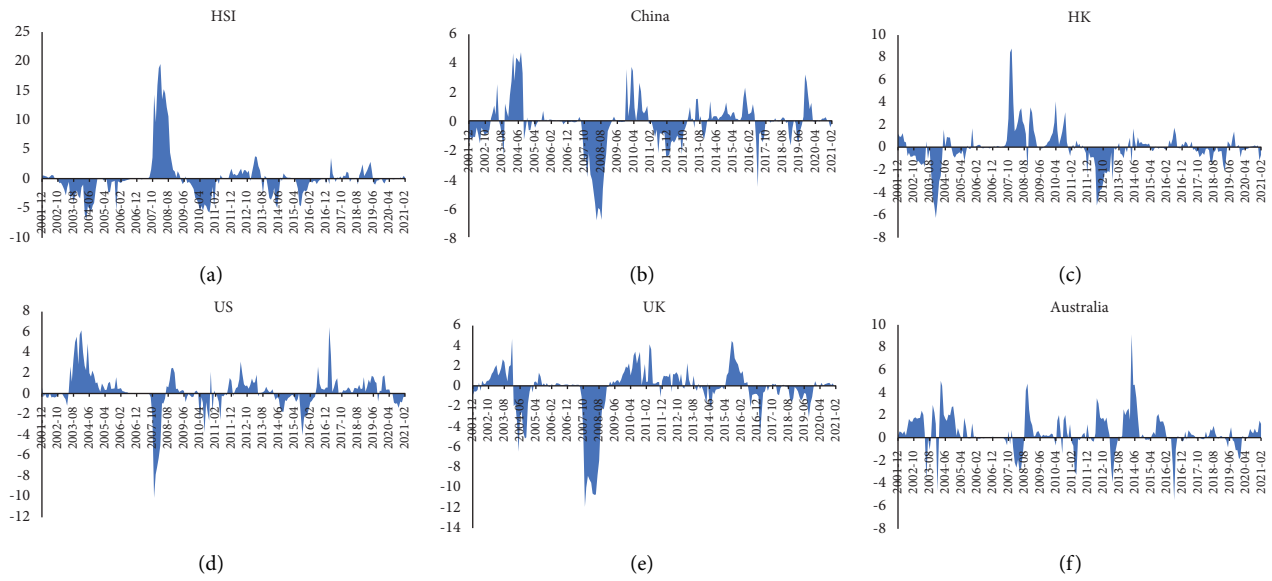

Figure 25: Long-term dynamic net spillover of Shanghai composite index and EPU.

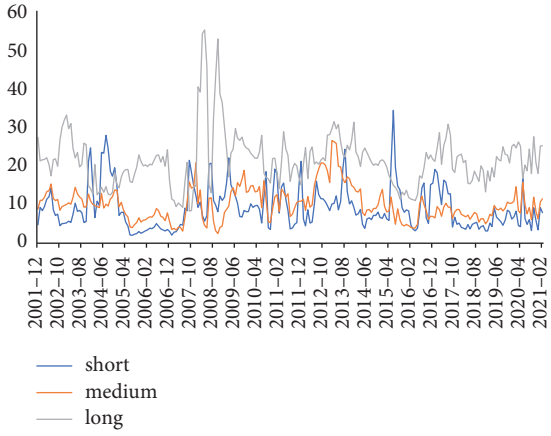

Figure 26: Dynamic total frequency connection between Shanghai composite index and EPU index.

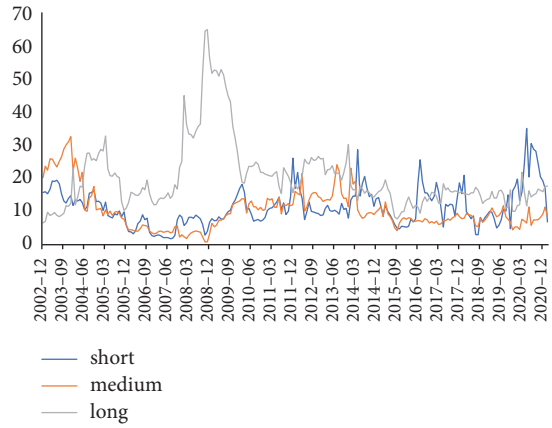

Figure 27: Dynamic total frequency connection between HSI and EPU index.

Table 11: Uncertainty of international economic policy and static short-term (0–3 months) spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
SSEC	15.01	0.09	0.03	0.16	0.08	0.25	0.1	0.6
China	0.1	9.62	0.06	0.09	0.02	0.16	0.07	0.44
HK	0.12	0.35	25.45	1.09	0.25	1.27	0.51	3.09
US	0.15	0.26	0.48	11.82	1.36	1.95	0.7	4.2
UK	0.02	0.06	0.09	1.19	9.58	1.32	0.45	2.67
Australia	0.17	0.02	0.72	2.29	1.75	12.52	0.82	4.95
TO_ABS	0.09	0.13	0.23	0.8	0.58	0.82	2.66	
TO_WTH	0.57	0.77	1.39	4.82	3.45	4.95		15.95

Table 12: Uncertainty of international economic policy and static medium-term (4–12 months) spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
SSEC	24.22	0.12	0.07	0.42	0.08	0.47	0.19	0.95
China	0.04	4.82	0.15	0.32	0.19	0.2	0.15	0.74
HK	0.28	0.38	20.65	1.3	0.34	2.27	0.76	3.76
US	0.14	0.32	0.8	14.27	2.68	6.05	1.67	8.21
UK	0.03	0.12	0.41	1.79	11.27	2.62	0.83	4.09
Australia	0.3	0.06	0.95	3.97	3.46	16.18	1.46	7.18
TO_ABS	0.13	0.17	0.4	1.3	1.13	1.94	5.06	
TO_WTH	0.66	0.82	1.95	6.41	5.55	9.54		24.92

Table 13: Uncertainty of international economic policy and static long-term (more than 12 months) spillover index of Shanghai composite index.

	SSEC	China	HK	US	UK	Australia	FROM_ABS	FROM_WTH
SSEC	54.81	1.34	0.3	1.02	0.62	0.91	0.7	1.11
China	0.43	48.39	5.63	9.75	11.42	8.61	5.97	9.47
HK	1.15	9.66	25.11	2.47	2.99	4.85	3.52	5.58
US	0.08	8.38	2.43	20.9	11.05	16.89	6.47	10.26
UK	0.71	10.33	4.36	9.86	31.81	14.42	6.62	10.49
Australia	0.52	2.6	2.79	10.11	11.77	29.81	4.63	7.35
TO_ABS	0.48	5.38	2.59	5.54	6.31	7.61	27.91	
TO_WTH	0.77	8.54	4.1	8.78	10.01	12.07		44.27

stock market is 0.1% in the short term (0–3 months), 0.19% in the medium term (4–12 months), and 0.7% in the long term (more than 12 months). On the other hand, the spillover relationship between EPU and stock market has time-varying characteristics. For the Shanghai stock market, the degree of spillover of EPU is larger in the United States (0.16% and 0.42%) and Australia (0.25% and 0.47%) in the short- and medium-term frequency. In the long-term frequency, China's EPU spillover to it is 1.34%. This is consistent with the result of static spillover in frequency domain with lag order 2, so it can be considered that the empirical conclusion is robust under the condition of model parameters with lag order 2.

6. Conclusions

In the era of rapid development of information technology, the research on the relationship between EPU and the stock market and risk spillover effect plays an important role in the improvement of financial risk management and portfolio optimization. However, the existing research focuses on the market risk from the time-domain framework, ignoring the frequency characteristics of market risk contagion. The main purpose is to study the direction and degree of risk spillover of international EPU on the stock market by using wavelet coherence and frequency-domain framework, respectively, taking Shanghai and Hong Kong stock market as research objects, to reveal the risk factors of Chinese stock market and put forward reasonable and effective control suggestions for different stock markets.

This paper selects China, the United States, Australia, and the United Kingdom and uses the monthly EPU index of these countries or regions. The 5-minute high-frequency realized volatility of the SSEC and HSI is used to analyze the dynamic spillover effects of international EPU on the stock market. The main conclusions of this paper are as follows.

First, the EPU and the dependence of the stock market are obviously different in the time domain and frequency domain, and the phase arrow is constantly changing, indicating that the lead-lag relationship between them has time-varying characteristics. Among them, the EPU of the Shanghai and Hong Kong is the strongest, followed by the EPU of US and Australia. On the other hand, the Hong Kong stock market and the United Kingdom have the strongest dependence on the HSI. Therefore, policymakers and portfolio managers should pay attention to the policy fluctuations of China's offshore financial markets and overseas countries and improve the risk link information sharing and supervision mechanism.

Second, the long-term effects of EPU and stock market risk spillover are dominant, and the EPU and risk spillover in the Hong Kong stock market is stronger than those in the Shanghai stock market. For the Shanghai stock market, the EPU of the US, Britain, Hong Kong, and Australia is mainly the sender of risk spillover, while the EPU of China is mainly the receiver. In the Hong Kong stock market, the HSI is mainly the sender of risk spillover. Therefore, market investors are required to constantly optimize investment strategies for different stock markets, consider the persistence of risk spillover, and better guard against financial risks.

Third, the EPU and the frequency-domain risk net spillover of the stock market have frequency characteristics, while the positive and negative alternation of the net risk spillover indicates that there is a two-way and asymmetric risk spillover between them. Similarly, net risk spillover has long been dominant. The outbreak of the crisis has increased the risk of spillover between the two. Therefore, the country should strengthen the emergency mechanism to deal with the crisis so that the market investors can better deal with the crisis.

This paper hopes to improve the management strategies for different stock markets as much as possible by comparing and analyzing the time-frequency risk spillover effects of EPU on the Shanghai and Hong Kong stock market, so as to provide higher risk management measures for the stock market and provide scientific and reasonable reference and support for investors of different investment portfolios. Based on the above research, this paper still has some shortcomings and fails to explore the main factors leading to the difference between the Hong Kong and the Shanghai stock market, which will become the main content of the next step of this paper.

Section 6 clearly explains the main findings and implications of the work, highlighting its importance and relevance.

Data Availability

The data sample spans from January 2000 to February 2021, excluding a total of 254 missing values. This paper uses the monthly economic policy uncertainty index compiled by Baker et al. [1], derived from https://www.policyuncertainty.com, and 5-minute high-frequency data from https://www.realized.Oxford-man.ox.ac.uk/.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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Research Article

Research on the Impact of Sino-US Trade Structure on the Real Effective Exchange Rate of RMB

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Since the beginning of 2018, Sino-US trade frictions have been escalating to the fields of science and technology, finance, and geography. Especially in the financial field, the United States has forcibly identified China as a "currency manipulator." In order to analyze the impact of Sino-US trade on the RMB exchange rate, based on the Sino-US import and export trade data under the quarterly HS classification from 2003 to 2019 and the RMB real effective exchange rate, this article carries out the traditional time series test, seasonal unit root test, and cointegration test and further constructs the seasonal error correction model to explore the long-term and short-term dynamic impact of Sino-US import and export trade structure on RMB real effective exchange rate. The results shows that the upgrading and optimization of the overall trade structure between China and the United States will increase the appreciation pressure of RMB real effective exchange rate. There are seasonal and long-term trends between RMB real effective exchange rate and different types of import and export trade structures between China and the United States. Therefore, this article not only strongly refutes the "theory of RMB appreciation" and puts forward policy suggestions to effectively deal with the negative impact of Sino-US trade friction but also provides a research framework for global trade, especially the decoupling of trade structure and exchange rate between developing and developed countries.

1. Introduction

Western media have long attributed the huge Sino-US trade surplus to exchange rate distortions caused by the artificial undervaluation of the RMB. Based on this, the "RMB appreciation theory" believes that RMB appreciation can reduce the scale of the Sino-US trade surplus, which is conducive to achieving a balance of US trade balance (Krugman, Jaime and John, and Won and Renan, respectively [1–3]). Since 2018, the Sino-US trade friction has intensified, and the relationship between the RMB exchange rate and the Sino-US trade balance has once again become the focus of discussion in the public and academic circles, and calls for the appreciation of the RMB continue to rise. However, only paying attention to the impact of the RMB exchange rate on the scale of trade balances will inevitably be biased. To fundamentally solve trade imbalances, we must also pay attention to the issue of trade structure imbalances. Most existing studies have focused on the relationship between total trade volume and the exchange rate. There are few studies on the relationship between trade structure and exchange rate. Few scholars have studied the RMB exchange rate from the perspective of Sino-US trade structure. Therefore, from the perspective of the Sino-US trade structure, this article clarifies the relationship between the Sino-US trade structure and the RMB exchange rate. It has profound theories for distinguishing the Sino-US exchange rate disputes and adjusting the Sino-US trade structure imbalance, and forming a mutually beneficial and win-win trade model is of far-reaching theoretical and practical significance.

2. Literature Review

At present, scholars have carried out fewer studies on the impact of trade structure on the RMB exchange rate, and the theoretical basis is the "Balassa-Samuelson" effect. The "Balassa-Samuelson" effect is that two scholars, Balassa and

Samuelson, explain the trend of real exchange rates from the perspective of relative production efficiency. There are differences in the rate growth rate. When a country's economy grows rapidly, that is, when the production efficiency of the trade sector increases significantly, it is often accompanied by an increase in the real exchange rate and an appreciation of the national currency.

Quan corrected the "Balassa-Samuelson" effect by reviewing the evolution of the trade structure and exchange rate in the course of Japan's modernization. He believed that the upgrading of the export structure was the main reason for the appreciation of the currency. Under the conditions of a substantial appreciation, China should adopt measures to restrict exports on its own to ease trade frictions [4]. Pan and Xu established a theoretical model of the effect of industrial transfer on real exchange rate changes and conducted empirical tests on the actual situation in Japan since the 1960s and the actual situation in China since the 1980s. The results confirmed that the "Balassa-Samuelson" effect is established in China; that is, the increase in the real exchange rate brought about by the increase in labor productivity of tradable goods exists in China [5]. Ma and Xu conducted a Granger causality test on China's quarterly data from 1980 to 2003 and found that there is a cointegration relationship between the real effective exchange rate of the RMB and China's export structure and that China's export structure is a Granger of the RMB exchange rate. Jie's reason can explain the changes in the RMB exchange rate to a certain extent [6]. Wang et al. conducted an empirical study on the relationship between the Sino-US trade structure and the RMB real effective exchange rate based on the annual data of the Sino-US trade structure and the RMB real effective exchange rate from 1980 to 2004. The results showed that China's total trade structure and export trade structure and the RMB real exchange rate are Granger causal to each other, and there is no cointegration relationship between the import trade structure and the RMB real exchange rate [7]. Xie and Liu found that there is an interactive relationship between the RMB real exchange rate and China's import and export trade. Adjusting the structure of China's international trade balance can effectively reduce the imbalance of the RMB real exchange rate and alleviate trade frictions between countries [8]. Marseilles added the trade structure to the purchasing power parity theory, emphasizing that the trade structure is effective on the equilibrium exchange rate through the wage effect and the wealth effect, and it is proved by the establishment of a three-sector economic model and the data of 264 countries from 1995 to 2018. An improvement in the trade structure will indeed lead to an appreciation of the equilibrium exchange rate [9]. Jin established the Redux model and found that the real exchange rate of the RMB can withstand various shocks under the conditions of open trade and maintain stability. With the optimization of the trade structure, the effect of restraining the fluctuation of the real exchange rate of the RMB will become stronger [10]. In addition, the depth and breadth of some scholars' research on trade are increasing. Wang and Han based their research on the decoupling of economic growth and carbon emissions between China and the United States (Wang et al.), by using multiregional input-output (MRIO), Tapio decoupling model, and structural decomposition analysis (SDA) to study the decoupling and driving factors of carbon emissions in Sino-US trade; it is found that the carbon emission decoupling reflected in China's exports to the United States is relatively unchanged and gradually improved, while the carbon emission decoupling reflected in the United States' exports to China is variable [11, 12].

Although the above-mentioned scholars' research has provided some reference for exploring the influence of the Sino-US trade structure on the RMB exchange rate, there are still the following shortcomings. First, the existing literature mostly pays attention to the total index data of trade balance and does not fully consider the differences in the trade structure reflected by the heterogeneity of different commodities. Second, most of the time periods covered by existing studies started from the 1990s to 2008 after the outbreak of the global financial crisis and did not cover the time period after the escalation of Sino-US trade frictions, so there is a lack of timeliness. Third, in order to reduce the loss of data information, existing studies mostly use actual data without seasonal adjustments when adopting traditional measurement methods. However, both exchange rate and trade structure data have significant seasonal characteristics, and data that does not eliminate seasonality will inevitably lead to potential relationships between related variables being incorrectly estimated and inferred. Based on this, this article uses the "Balassa-Samuelson" effect as the theoretical basis, using traditional time series testing and seasonal testing to explore the impact of the overall trade structure of China and the United States and the structure of different types of import and export trade between China and the United States on the real effective exchange rate of the RMB. First of all, this article uses the relative ratio of the high-productivity product rates in the import and export trade sectors of China and the United States, that is, the relative ratio of capital-intensive import and export trade under the HS classification standard to express the overall trade structure of China and the United States, and analyzes the overall trade structure of China and the United States, as well as whether it has an impact on the real effective exchange rate of the RMB and whether it conforms to the "Balassa-Samuelson" effect. Secondly, according to the HS classification standard, the Sino-US trade products are further classified into the quarterly data of China's capital-intensive, resource-intensive, and labor-intensive export and import trade with the United States. The seasonal cointegration test and seasonal error correction model are used to study the differences between China and the United States, as well as the impact of the structure of import and export trade on the long- and short-term dynamics of the real effective exchange rate of the RMB. Compared with the simple time series error correction model, this model can comprehensively analyze the dynamic evolution mechanism between Sino-US import and export trade structure and RMB real effective exchange rate on the premise of considering the heterogeneity of import and export trade of various products and the possible multiple long-term cointegrations relationship between relevant variables at different frequencies. Finally, based on

the empirical results of the above two parts, corresponding policy recommendations are put forward for Sino-US trade frictions.

3. Theoretical Model

The "Balassa-Samuelson" effect is a hypothesis explaining the relationship between exchange rate changes and productivity. The model mainly assumes complete competition in the commodity market, free flow of domestic factor sectors across sectors, and the establishment of the law of one price for traded goods. The theoretical derivation is as follows: P, P^* represent the price levels of the two countries, respectively, and the tradable-goods sector and the nontradable-goods sector are denoted by subscripts T and N, respectively. The price level of a country can be obtained by the weighted average of the price of traded goods and the price of nontraded goods. Then the price levels of the two countries can be expressed as equations (1) and (2), respectively, where θ and $1-\theta$ are the prices of traded goods and the weight of the price of nontradable goods.

$$P = (P_T)^{\theta}(P_N)^{1-\theta}, \tag{1}$$

$$P^* = (P_T^*)^{\theta}(P_N^*)^{1-\theta}. \tag{2}$$

Under open conditions, the price of trade products must meet $P_T = P_T^*$, as shown in the following formula:

$$\frac{P}{P^*} = \left(\frac{P_T}{P_T^*}\right)^{\theta}\left(\frac{P_N}{P_N^*}\right)^{1-\theta} = \left(\frac{P_N}{P_N^*}\right)^{1-\theta}. \tag{3}$$

The logarithm of equation (3) is taken to obtain the following equation:

$$P - P^* = (1-\theta)(P_N - P_N^*), \tag{4}$$

$$Y_i = A_i K_i^{\alpha_i} L_i^{1-\alpha_i}, \tag{5}$$

$$\mathrm{LR} = P_i^* Y_i - wL_i - rK_i. \tag{6}$$

Assuming that $P_T = P_T^* = 1$, the optimal first-order conditions of the traded-goods sector and the nontraded-goods sector are equations (7) and (8), in which the per capita capital $k_i = (K_i/L_i)$.

$$A_T(k_T)^{\alpha_T} = W + rk_T, \tag{7}$$

$$P_N A_N (k_N)^{\alpha_N} = W + rk_N. \tag{8}$$

The logarithm of equations (7) and (8) is taken to obtain equations (9) and (10), where U_{Li} represents the share of labor income in the production sector.

$$A_T \alpha_T = WU_{LT}, \tag{9}$$

$$P_N A_N \alpha_N = WU_{LN}. \tag{10}$$

From formulas (9) and (10), the following formula can be obtained:

$$P = \frac{U_{LN}}{U_{LT}}\frac{\alpha_T}{\alpha_N}A_T - A_N. \tag{11}$$

Substituting formula (11) into formula (4), we get the following formula:

$$P - P^* = (1-\theta)\left[\frac{U_{LN}}{U_{LT}}\frac{\alpha_T}{\alpha_N}(A_T - A_T^*) - (A_N - A_N^*)\right]. \tag{12}$$

The labor intensity of the nontradable-product sector is generally higher than that of the tradable-product sector; namely, $\alpha_N < \alpha_T$; that is, $U_{LN} > U_{LT}$.

Assuming that the production factors of the tradable and nontradable sectors are capital and labor, the production function and profit function with constant returns to scale of the two sectors can be expressed by equations (5) and (6), respectively, where A_i represents the total factor productivity of the two sectors; $i = T$ or N.

The changes in the productivity of the tradable sector are ultimately reflected in the trade structure. According to the "International Trade Standard Classification," a country's trade products can be divided into capital-intensive, labor-intensive, and resource-intensive products. It is generally believed that labor-intensive products have low technical content, and the increase in the proportion of capital-intensive products can represent an increase in the productivity level of the traded goods sector, thereby increasing the real exchange rate level. In a country with rapid economic growth, the proportion of capital-intensive products in its trade structure will inevitably continue to increase, so that the productivity of the country's trade product sector is also constantly improving. Therefore, based on the above analysis of the main conclusions of the "Balassa-Samuelson" effect, we can draw the following conclusions: changes in a country's trade structure will affect changes in a country's real exchange rate.

4. Samples and Variables

4.1. Explanatory Variable: Structural Variables of Sino-US Trade. According to the HS classification standard, this article classifies Sino-US trade products into capital-intensive, labor-intensive, and resource-intensive products. Among them, capital-intensive products include categories 16, 17, and 18 in the HS classification standard, labor-intensive products include categories 7, 8, 9, 11, and 12 in the HS classification standard, and resource-intensive products include categories 5, 6, 13, and 15 in the HS classification standard. Capital-intensive imports, labor-intensive imports, and resource-intensive imports are represented by IZBMJ, ILDMJ, and IZYMJ, respectively, and capital-intensive exports, labor-intensive exports, and resource-intensive exports are represented by EZBMJ, ELDMJ, and EZYMJ, respectively.

This article defines capital-intensive products as high-productivity products and labor-intensive and resource-intensive products as low-productivity products. The rate of high-productivity products in China's export trade to USA

represents China's export structure to the US CTTA; namely, CTTA = (EZBMJ/EZBMJ + ELDMJ + EZYMJ). The rate of high-productivity products in China's import trade with the United States represents the ATTC of China's import structure to the United States; namely, ATTC = (IZBMJ/IZBMJ + ILDMJ + IZYMJ).

Since the overall Sino-US trade structure (TS) is negatively correlated with the import trade structure and positively correlated with the export trade structure, the overall Sino-US trade structure can be expressed by the ratio of the export trade structure to the import trade structure; namely,

$$\mathrm{TS} = \frac{\mathrm{CTTA}}{\mathrm{ATTC}}. \tag{13}$$

The quarterly trade data used in this article from 2003 to 2019 are all from the China Economic Network database.

4.2. Explained Variable: Real Effective Exchange Rate of RMB. The real effective exchange rate of RMB is the real effective exchange rate after adjusting the relative price level between China and the United States. The calculation formula is REER = $(P/E * P^*)$, where P represents the price level in China, P^* represents the price level in the United States, and E represents the nominal exchange rate expressed by the direct price method. The increase in the real effective exchange rate of the RMB means the appreciation of the RMB and an increase in the purchasing power of the RMB.

The quarterly data on the real effective exchange rate of RMB used in this article from 2003 to 2019 come from the IFS database of the International Monetary Fund (IMF).

5. Results and Discussion

5.1. An Empirical Test of the Impact of Sino-US Trade Structure on the Real Effective Exchange Rate of RMB

5.1.1. Stationarity Test. This article takes the natural logarithm of the variables related to the Sino-US trade structure and the real effective exchange rate of the RMB and then performs the ADF unit root test. The results are shown in Table 1. The first-order difference between the overall Sino-US trade structure, China's import structure to the United States, China's export structure to the United States, and the real effective exchange rate of the RMB is significant at the 5% level, indicating that they are a stationary series after the first-order difference.

Table 1: Stationarity test.

Variables	Test equation form	ADF	Conclusion
DINREER	$(C, T, 0)$	-10.1^{***}	Yes
DINTS	$(C, T, 2)$	-12.1^{***}	Yes
DATTC	$(C, T, 1)$	-12.5^{***}	Yes
DCTTA	$(C, T, 4)$	-10.9^{***}	Yes

Note. The form of the test equation is (C, T, L), where C, T, and L represent the constant term, the trend term, and the lag order, respectively; the selection of the optimal lag order is based on the AIC and SC criteria. T statistics are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

5.1.2. Cointegration Test. The cointegration test results of TS, ATTC, CTTA, and REER (see Table 2) show that, at 5% significance level, the overall trade structure of China and the United States, the import structure of China to the United States, the export structure of China to the United States, and the real effective exchange rate of RMB are cointegrated. It can be seen from equation (14) that the coefficient of the overall trade structure variable between China and the United States is positive, indicating that the upgrading of the overall trade structure between China and the United States has a positive effect on the real effective exchange rate of the RMB; that is, the upgrading of the overall trade structure between China and the United States will promote the appreciation of the RMB. This result is consistent with the description of the "Balassa-Samuelson" effect. For every 1 percentage point improvement in the overall trade structure of the US and China, the real effective exchange rate of the RMB rose by 6.14 percentage points. According to formula (15), for every 1 percentage point improvement in the structure of China's import trade with the United States, the real effective exchange rate of the RMB drops by 4.64 percentage points. According to formula (16), for every 1 percentage point improvement in the structure of China's export trade with the United States, the real effective exchange rate of the RMB drops by 15.2 percentage points. The results of formulas (15) and (16) show that the structure of China's import trade with the United States and the structure of its export trade only partly reflect the changes in productivity in the tradable sector and indirectly affect the real effective exchange rate of the RMB (Wang et al. [7]); the assumptions that embody the Balassa-Samuelson effect do not match China's reality (Yang, Hu, and Zeng, Lu and Liu, Lin, and Bu, respectively [13–17]). The "Balassa-Samuelson" effect requires the free flow of capital and at the same time requires the product market to be a perfectly competitive market. However, in fact, due to the distortion of the market system and capital control in China, the "Balassa-Samuelson" effect may be possibly suppressed or amplified.

$$\mathrm{INREER} = \underset{(1.149)\quad(0.089)}{6.142\mathrm{INTS} - 4.658}, \tag{14}$$

$$\mathrm{INREER} = \underset{(1.011)\quad(0.502)}{-4.636\mathrm{INATTC} - 6.900}, \tag{15}$$

$$\mathrm{INREER} = \underset{(1.446)\quad(0.713)}{-15.15\mathrm{INCTTA} - 12.08}. \tag{16}$$

5.1.3. Robustness Test. This article replaces the Sino-US trade structure (TS) classified according to the HS classification standard in the original model with the Sino-US trade structure (RTS) classified according to the SITC standard, that is, the ratio of China's export structure to the United States and China's import structure to the United States. China's export structure to the United States and the import structure, respectively, represent the proportion of manufactured goods in China's import trade and export trade with

Table 2: Cointegration test results.

Variables	Trace statistics	p value	5% level	Number of cointegration equations
(INREER, INTS)	28.19	0.003	20.26	None
	2.723	0.633	9.164	At most one
(INREER, INATTC)	21.66	0.040	20.26	None
	2.957	0.588	9.164	At most one
(INREER, INCTTA)	86.92	0.001	20.26	None
	2.227	0.732	9.164	At most one

the United States. The last five categories of the Standard International Trade Classification (SITC) are industrial finished products, followed by chemical (finished) products and related products, as well as finished products classified by raw materials (mainly related to textile products, rubber products, mining and metallurgical products, and related products), machinery and transportation equipment, miscellaneous products, and unclassified (other) commodities. The empirical results after the replacement of the data classification standard are shown in equation (17). The t value is greater than 1.96, indicating that the replacement variable is significant at the 5% level and the coefficient sign is positive, which is consistent with the original model test result, so the model passed the robustness test.

$$\text{INREER} = \underset{(0.086)\quad(0.033)}{0.748\text{INRTS} + 4.368}. \tag{17}$$

5.2. An Empirical Test of the Impact of Different Types of Import and Export Trade Structures between China and USA on the Real Effective Exchange Rate of RMB. Since the traditional time series analysis method cannot fully mine and make use of the rich information contained in the time dimension of high-frequency trade data, the potential multiple cointegrations relationship between RMB exchange rate and trade structure at different frequencies is ignored. Therefore, this article uses seasonal test to make a comprehensive dynamic analysis of Sino-US trade structure on RMB real effective exchange rate from a higher heterogeneous classification level. Based on the HS classification standard, Sino-US trade products are further divided into quarterly data of China's capital-intensive, resource-intensive, and labor-intensive exports and imports to the United States. On this basis, the seasonal unit root test, seasonal cointegration test, and seasonal error correction model are used to study the long-term and short-term dynamic effects of different types of import and export trade structures between China and the United States on the real effective exchange rate of RMB. For the specific empirical process, we refer the reader to the works of Hylleberg et al., Joseph and Miron, and Su and Lu, respectively [18–20].

5.2.1. HEGY Seasonal Unit Root Test. It can be seen from Figure 1 that the import and export trade of different types of products between China and the United States has obvious seasonal characteristics, so this article uses the HEGY seasonal unit root test.

The idea of HEGY test is to realize the simultaneous test of the unit root of 0 frequency and seasonal frequency by factoring the seasonal difference operator $(1 - L^s)$ on different seasonal frequencies. When using seasonal data, the method of seasonal difference should be used to make the series stable. The difference equation is $y_t - y_{t-4} = (1 - L^4)y_t$, $(1 - L^4)$ is a seasonal operator. This article constructs the regression equation of the HEGY seasonal unit root test as follows:

$$\left(1 - L^4\right)y_t = \mu_t + \pi_1 y_{1,t-1} + \pi_2 y_{2,t-1} + \pi_3 y_{3,t-2} + \pi_4 y_{3,t-1} + \varepsilon_t. \tag{18}$$

Here, μ_t is composed of constant items, seasonal dummy variables, and trend items; π_i $(i = 1, 2, 3, 4)$ is the regression coefficient; ε_t is white noise; y_t contains 4 unit roots; that is, at 0 frequency, the unit root is +1; at 1/2 frequency, the unit root is −1; at 1/4 frequency, the unit root is $\pm i$. $(1 - L^4) = (1 - L)(1 + L)(1 + L^2)$, $y_{1,t} = (1 + L + L^2 + L^3)y_t$, $y_{2,t} = -(1 - L + L^2 - L^3)y_t$, and $y_{3,t} = -(1 - L^2)y_t$. The test includes 3 null hypotheses: $\pi_1 = 0, \pi_2 = 0, \pi_3 = \pi_4 = 0$. π_1, π_2 is the t-test statistic; π_3, π_4 is the F joint test statistic. The test critical value refers to the research results of Hylleberg et al. [18], which are used to test unit roots with frequencies of 0, 1/2, and 1/4, respectively. The results of the seasonal unit root test of China's import and export trade structure of capital-intensive, labor-intensive, and resource-intensive products of the United States and the real effective exchange rate of RMB are shown in Table 3.

5.2.2. Seasonal Cointegration Test and Long-Term Impact Test. Since all variables contain seasonal unit roots, it is shown that there may be a cointegration relationship between the China-USA import and export trade structure and the real effective exchange rate of RMB at frequencies of 0, 1/2, and 1/4. The EG two-step method is used to perform the following cointegration test on the three frequencies of 0, 1/2, and 1/4.

At frequencies of 0, 1/2, and 1/4, the cointegration test regressions of China's capital-intensive, labor-intensive, and resource-intensive import and export trade structure against the real effective exchange rate of the RMB to the United States are, respectively, shown in the two following equations:

$$\text{INREER}_{it} = \alpha_{it} I_{it} + \varepsilon_{it-I}, \tag{19}$$

$$\text{INREER}_{et} = \beta_{et} E_{et} + \varepsilon_{et-E}. \tag{20}$$

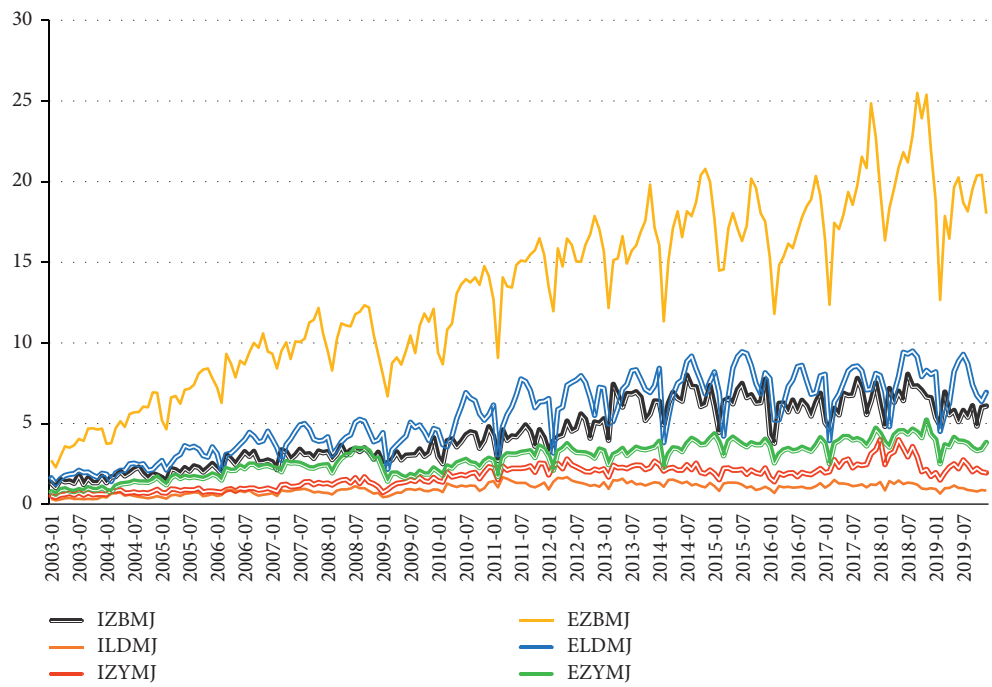

Figure 1: Seasonal characteristics of import and export trade of different types of products between China and the United States.

Table 3: HEGY test results.

	INIZBMJ	INEZBMJ	INILDMJ	INELDMJ	INIZYMJ	INEZYMJ	INREER
$t_{\pi 1}$	1.121	−0.109	−0.460	−0.003	−1.523	0.040	−1.329
Conclusion	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$t_{\pi 2}$	−0.509	1.605	0.339	0.388	1.935	1.161	1.518
Conclusion	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$F_{2(\pi 3,\pi 4)}$	1.618	1.234	0.323	2.086	0.425	0.261	1.421
Conclusion	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Here, $i, e = 1, 2, 3$ correspond to the data of 0 frequency, 1/2 frequency, and 1/4 frequency of the inlet and outlet, respectively; $Y_{1t} = (1 + L + L^2 + L^3)Y_t, I_{1t} = (1 + L + L^2 + L^3)I_t, E_{1t} = (1 + L + L^2 + L^3)E_t; Y_{2t} = -(1 - L + L^2 - L^3)Y_t, I_{2t} = -(1 - L + L^2 - L^3)I_t, \quad E_{2t} = -(1 - L + L^2 - L^3) \quad E_t; Y_{3t} = -(1 - L^2)Y_t, I_{3t} = -(1 - L^2)I_t, E_{3t} = -(1 - L^2)E_t;$ $Y = \text{INREER}$, $I = \text{INIZBM}$, INILDMJ, INIZYMJ, $E = \text{INEZBMJ}$, INELDMJ, INEZYMJ. If the residuals of the above equations $\varepsilon_{it-I}, \varepsilon_{et-E}$ are all stable, then the above equation is the cointegration equation of RMB real effective exchange rate and China's capital intensive, labor-intensive, and resource intensive import and export trade structure to the United States at the frequency of 0, 1/2, and 1/4, respectively.

The test results of the cointegration relationship between the real effective exchange rate of RMB and the capital-intensive, labor-intensive, and resource-intensive import and export trade structure of China to the United States at 0, 1/2, and 1/4 frequencies are shown in Table 4. At frequencies of 0, 1/2, and 1/4, the residuals of the cointegration regression between the real effective exchange rate of RMB and the capital-intensive, labor-intensive, and resource-intensive import and export trade structures are all stable; that is, equations (19) and (20) are the cointegration equations between the real effective exchange rate of RMB and the structure of China's import and export trade of capital-intensive, labor-intensive, and resource-intensive products with the United States. China's capital-intensive, labor-intensive, and resource-intensive import and export trade structure with the United States has a long-term cointegration relationship with the real effective exchange rate of RMB at 0, 1/2, and 1/4 frequencies, that is, capital at seasonal and nonseasonal frequencies. There is a long-term equilibrium relationship between the import and export trade structure of capital-intensive, labor-intensive, and resource-intensive products and the real effective exchange rate of RMB. At the frequencies of 0, 1/2, and 1/4, the capital-intensive, labor-intensive, and resource-intensive import and export trade structures are the long-term influencing factors of the real effective exchange rate of the RMB.

5.2.3. Seasonal Error Correction Model and Short-Term Impact Relationship Test. This article further analyzes the short-term causal relationship between the import and export trade structure of different types of products of China

Table 4: Tests on the 0, 1/2, and 1/4 frequency cointegration.

		ZBMJ		LDMJ		ZYMJ	
0	t value	$\varepsilon_{1t-\mathrm{INIZBMJ}}$ −2.380* Yes	$\varepsilon_{1t-\mathrm{INEZBMJ}}$ −2.722* Yes	$\varepsilon_{1t-\mathrm{INILDMJ}}$ −1.932* Yes	$\varepsilon_{1t-\mathrm{INELDMJ}}$ −2.050** Yes	$\varepsilon_{1t-\mathrm{INIZYMJ}}$ −2.578*** Yes	$\varepsilon_{1t-\mathrm{INEZYMJ}}$ −2.748*** Yes
1/2	t value	$\varepsilon_{2t-\mathrm{INIZBMJ}}$ −3.833* Yes	$\varepsilon_{2t-\mathrm{INEZBMJ}}$ −3.053** Yes	$\varepsilon_{2t-\mathrm{INILDMJ}}$ −2.868** Yes	$\varepsilon_{2t-\mathrm{INELDMJ}}$ −3.498*** Yes	$\varepsilon_{2t-\mathrm{INIZYMJ}}$ −2.390** Yes	$\varepsilon_{2t-\mathrm{INEZYMJ}}$ −3.543* Yes
1/4	t value	$\varepsilon_{3t-\mathrm{INIZBMJ}}$ −3.432** Yes	$\varepsilon_{3t-\mathrm{INEZBMJ}}$ −2.634* Yes	$\varepsilon_{3t-\mathrm{INILDMJ}}$ −4.748* Yes	$\varepsilon_{3t-\mathrm{INELDMJ}}$ −3.748** Yes	$\varepsilon_{3t-\mathrm{INIZYMJ}}$ −2.563** Yes	$\varepsilon_{3t-\mathrm{INEZYMJ}}$ −3.256* Yes

Note. The critical values of the seasonal cointegration test for all import and export trade structures determined in this article are as follows: the critical value of 1% is −2.605, the critical value of 5% is −1.946, and the critical value of 10% is −1.613; ***rejecting the nonstationary hypothesis at the 1% significance level, **rejecting the nonstationary hypothesis at the 5% significance level, and *rejecting the nonstationary hypothesis at the 10% significance level.

Table 5: Seasonal error correction model.

Variable	ZBMJ		LDMJ		ZYMJ	
	$\Delta_4\mathrm{INREER}_{it}$	$\Delta_4\mathrm{INREER}_{et}$	$\Delta_4\mathrm{INREER}_{it}$	$\Delta_4\mathrm{INREER}_{et}$	$\Delta_4\mathrm{INREER}_{it}$	$\Delta_4\mathrm{INREER}_{et}$
$\Delta_4\mathrm{INIZBMJ}_{it}$	0.040*					
$\Delta_4\mathrm{INEZBMJ}_{it}$		0.030*				
$\Delta_4\mathrm{INILDMJ}_{it}$			0.041**			
$\Delta_4\mathrm{INELDMJ}_{it}$				0.047*		
$\Delta_4\mathrm{INIZYMJ}_{it}$					0.044**	
$\Delta_4\mathrm{INEZYMJ}_{it}$						0.050***
ECM_0	−0.060*	−0.013*	−0.066**	−0.074*	−0.088**	−0.050*
$\mathrm{ECM}_{1/2}$	−0.090*	−0.091*	−0.039*	−0.007*	−0.047*	−0.018*
$\mathrm{ECM}_{1/4}$	−0.140**	−0.458**	−0.147**	−0.230**	−0.701***	−0.594***

Note. The model is shown. T statistics are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

and the United States and the real effective exchange rate of the RMB by constructing a seasonal error correction model, as well as the adjustment strength of the short-term deviation of related variables to the long-term equilibrium, and constructs a model as shown in the two following equations:

$$\Delta_4\mathrm{INREER}_{it} = C_i + \Delta_4\mathrm{INI}_t + \lambda_1\mathrm{ECM}_{i,0} + \lambda_2\mathrm{ECM}_{i,(1/2)} + \lambda_3\mathrm{ECM}_{i,(1/4)}, \tag{21}$$

$$\Delta_4\mathrm{INREER}_{et} = D_i + \Delta_4\mathrm{INE}_t + \eta_1\mathrm{ECM}_{e,0} + \eta_2\mathrm{ECM}_{e,(1/2)} + \eta_3\mathrm{ECM}_{e,(1/4)}. \tag{22}$$

Here, $I = \mathrm{INIZBMJ}, \mathrm{INILDMJ}, \mathrm{INIZYMJ}$; $E = \mathrm{INEZBMJ}, \mathrm{INELDMJ}, \mathrm{INEZYMJ}$; error correction terms $(\mathrm{ECM}_{i,0}, \mathrm{ECM}_{i,(1/2)}, \mathrm{ECM}_{i,(1/4)})$, respectively, represent the residuals of the cointegration relationship between the real effective exchange rate of RMB and China's capital-intensive, labor-intensive, and resource-intensive import trade structure with the United States at 0, 1/2, and 1/4 frequencies. In the same way, $\mathrm{ECM}_{e,0}, \mathrm{ECM}_{e,(1/2)}, \mathrm{ECM}_{e,(1/4)}$, respectively, represent the residuals of the cointegration relationship between the real effective exchange rate of RMB and China's capital-intensive, labor-intensive, and resource-intensive export trade structure to the United States at 0, 1/2, and 1/4 frequencies. If the original hypothesis $(\eta_i = 0\ (i = 1, 2, 3))$ does not hold, it means that there is an error correction mechanism at 0, 1/2, and 1/4 frequencies, and vice versa. The lag period selected in this article is 1, and the results of the seasonal error correction are given in Table 5.

In the short term, China's capital-intensive, labor-intensive, and resource-intensive import and export trade structure with the United States is a short-term influencing factor of the real effective exchange rate of the RMB. The resulting appreciation pressure further verified the existence of the "Balassa-Samuelson" effect. In addition, the error correction models of capital-intensive, labor-intensive, and resource-intensive import and export trade structures at the frequencies of 0, 1/2, and 1/4 are negative numbers and all have passed the 10% significance test. There is a long-term equilibrium relationship between the import and export trade structure of similar products and the real effective exchange rate of RMB in both nonseasonal frequency and seasonal frequency. Different types of trade structures in nonseasonal frequency and seasonal frequency will have an impact on the real effective exchange rate of RMB. At the same time, the coefficient of the error correction term reflects the adjustment strength that deviates from the long-term equilibrium. The adjustment coefficient of the error correction term at 1/4 frequency is generally greater than the adjustment coefficient at 0 frequency and 1/2 frequency, indicating that capital-intensive, labor-intensive, and resource-intensive short-term changes have significantly greater adjustment strength for deviations from 1/4 frequency balance than deviations from 0 frequency and 1/2

frequency. As far as the Sino-US capital-intensive import trade structure is concerned, at 0 frequency, when short-term fluctuations deviate from the long-term equilibrium, the 6.03% deviation of the RMB's real effective exchange rate from the long-term equilibrium will be adjusted. At the frequency of 1/2, the deviation of the real effective exchange rate of RMB from 9.02% of the long-term equilibrium will be adjusted. At the frequency of 1/4, the deviation of the real effective exchange rate of RMB from the long-term equilibrium of 14.08% will be adjusted.

6. Conclusions

First of all, based on the "Balassa-Samuelson" effect, this article uses the cointegration method to test the impact of the overall trade structure of China and the United States on the real effective exchange rate of the RMB and finds that the overall trade structure between China and the United States has a positive correlation with the real effective exchange rate of the RMB. That is to say, the upgrading and optimization of the overall trade structure between China and the United States will increase the pressure on the appreciation of the real effective exchange rate of the RMB. Secondly, seasonal cointegration test is performed and seasonal error correction model is constructed to further verify the mechanism of Sino-US capital-intensive, labor-intensive, and resource-intensive import and export trade structure on the real effective exchange rate of RMB. In terms of seasonal frequency, there are seasonal and long-term trends between the real effective exchange rate of RMB and different types of Sino-US import and export trade structures. The different types of Sino-US import and export trade structures are both the RMB real effective exchange rate at the long-term and short-term cyclical levels, factors affecting changes.

Different from the traditional research methods, the seasonal test model used in this article improves the effectiveness of the test from the spatial dimension and can accurately describe the fluctuation characteristics of Sino-US trade structure data in different frequencies from the time dimension, as well as the data generation characteristics of RMB real effective exchange rate; it is of great practical significance to formulate corresponding foreign economic development policies. Based on this, it can be considered that the theoretical model and empirical model of this article have confirmed the effectiveness of the conclusion, and the theory can become a tool to analyze the trend of RMB exchange rate, help government departments better predict the trend of exchange rate, and formulate more reasonable control policies on this basis, which has strong practical significance.

As China accelerates the construction of a new development pattern with the domestic big cycle as the main body and the domestic and international double cycles promoting each other, in order to effectively refute the "RMB appreciation theory" and effectively respond to the negative impact of Sino-US trade frictions, this article puts forward the following policy recommendations combined with the empirical results:

First, deepen the reform of the RMB exchange rate formation mechanism, and continue to maintain the two-way expectations and two-way flexibility of the RMB exchange rate. In the short term, although countercyclical factor adjustment can be used as a policy tool to stabilize exchange rate fluctuations and moderate market sentiment, using this tool too frequently will send negative signals to the market, leading to intensified expectations of RMB depreciation in the offshore market. Only by taking into account the flexibility and stability of the RMB exchange rate formation mechanism can the continuous deterioration of the Sino-US trade imbalance and the risk and pressure of the formation of the RMB exchange rate "overshoot" be avoided, and the RMB can be effectively hedged against Sino-US trade frictions and the strengthening of the US dollar index. The procyclical sentiment in the direction of devaluation prevents the rapid rise and fall of the RMB exchange rate from amplifying the impact of cyclical fluctuations in the import and export trade structure on trade, so as to better play the role of exchange rate adjustment macroeconomics and automatic balance of payments stabilizer.

Second, promote the upgrading of trade structure and develop new drivers of diversification and high-quality development of foreign trade. On the one hand, low-productivity sectors such as agricultural products have always been the focus of Sino-US trade frictions. Strengthen trade protection and production support for low-productivity sectors such as agriculture, focus on the expansion of import strategies, increase imports of low-productivity products, and properly handle the expansion of imports. The relationship between ensuring the safety of domestic industries and steadily advancing the construction of a strategic guarantee system for Chinese agricultural products under open conditions will help offset the devaluation pressure of the RMB exchange rate caused by the Sino-US trade friction. On the other hand, increase resource input and policy tilt in high-productivity sectors, achieve rapid breakthroughs in core technologies and key industries, promote the upgrading of trade structure with "brand strategy," cultivate international competitive advantages that extend to mid-to-high-end, and encourage Chinese companies going out, with the help of policy initiatives, such as the "One Belt, One Road" initiative, to broaden the foreign trade corridors for Chinese enterprises.

Third, prevent "false exports" brought about by export encouragement policies, and build a healthy and orderly export rule and market environment. Compared with investment channels and nontrade channels, foreign exchange barriers and risks under trade are small, and they have become the main channel for hot money to flow into China. "False exports" may not only cause the trade balance between China and the United States to be inflated but also put pressure on

the appreciation of the RMB. If the "export inflated" is dominated by capital-intensive products, it may produce a phenomenon of "false upgrades" in the trade structure; if the "export inflated" is dominated by labor-intensive and resource-intensive products, it may lead to an increase in the price level of such domestic products, which is unfavorable to the long-term development of export enterprises and the upgrading of the trade structure. Therefore, only by strengthening the identification and management of hot money inflows from import and export trade channels between China and the United States, strengthening the functions of import and export administrative agencies, and carefully formulating preferential import and export policies can the normal order of the development of the export-oriented industrialization be ensured, creating a fair international trade competition environment for export enterprises.

Fourth, realize the diversification of trade countries, strive to solve the development dilemma of Sino-US bilateral trade, actively participate in the negotiation and construction of regional economic integration, and establish good bilateral, plurilateral, and multilateral trade relations. We should continue to deepen the construction of "One Belt, One Road" and "Regional Comprehensive Economic Partnership" (RCEP), integrate into regional economic integration organizations, and give full play to the advantages of participating in regional economic integration, so as to promote the diversified development of China's foreign trade and serve China. Participate in the empowerment of international economic and trade cooperation in the future. At the same time, seize the opportunity to promote the negotiation of the China-Japan-Korea Free Trade Area Agreement, as well as in-depth discussion and analysis of the "Comprehensive and Progressive Agreement on Trans-Pacific Partnership" (CPTPP) trade rules, and conduct a systematic study on the possibility of China joining the agreement. Use this as a guarantee to offset US trade unilateralism and expand China's opening up.

Fifth, maintain the strategic determination of currency and trade policies, and work to resolve Sino-US trade frictions. The excessive import caused by the low cost of the US dollar will inevitably lead to successive years of trade deficits between the United States and China. At a time of extreme market volatility and lack of exposure to risks, the Chinese government should maintain the strategic focus of monetary policy, stabilize RMB exchange rate expectations, and increase foreign confidence in RMB assets in order to change the dollar-dominated world monetary pattern and fundamentally change the state of global trade imbalances. At the same time, trade policies must also maintain strategic determination. Under the premise of maintaining the balance of import and export trade, increase the competitive value and added value of exports and actively expand imports.

Data Availability

The processed data required to reproduce the findings of this paper cannot be shared at this time as the data also form part of an ongoing study.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

J. Y. and J. C. were involved in conceptualization, methodology, validation, formal analysis, and reviewing and editing. J. C. provided software and resources and carried out data curation and original draft preparation. J. Y. was responsible for investigation, visualization, supervision, project administration, and funding acquisition. Both authors have read and agreed to the published version of the manuscript.

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Research Article

The Complexity of Global Capital Flows: Evidence from G20 Countries

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With the high volatility of capital flow and the imbalance of capital flow between emerging and advanced economies, the complexity of capital flow management is always attractive to researchers and policymakers. This study explores how capital flows in G20 countries are significantly impacted by pull and push factors by using regressions, dynamic system GMM, and Panel-VAR models. The results show that international capital flows are significantly associated with domestic financial development, which is measured by stock-market liquidity and domestic credit. Moreover, international capital flows are affected by push factors, such as the growth of the world economy and fluctuations of the crude oil price. This study controls for real interest rate, foreign currency, and capital restriction because the government and macroprudential policies are critical influences on stabilizing capital flows.

1. Introduction

Since globalization accelerates capital integration between advanced and emerging economies after the 1970s, a large number of studies argue that capital flows from rich to poor countries. Capital inflows increase the standards of living and promote economic growth in developing nations. Moreover, international capital flows diversify investment portfolios and achieve a better return on pension funds and retirement accounts for developed countries. However, the capital inflows suddenly slowed down in the late 1990s, increased rapidly throughout the mid-2000s, contracted sharply during the 2007–2009 financial crisis, and then rebounded after 2010 [1]. Facing the high volatility of capital flow and the imbalance of capital flow between emerging and advanced economies, the complexity of capital flow management is always attractive to researchers and policymakers.

Some studies show that external factors are the primary drivers of capital flow, such as financial crisis, mature economy, interest rates, mature economic growth, and shocks in U.S. equity markets [2–5]. In the era of globalization, international capital flows are not only driven by mature economies but also impacted by global economic changes. By extending previous empirical evidence, this study hypothesizes that the international capital flows are impacted by external factors, such as world economic growth and the fluctuations of crude oil. Some studies, however, emphasize the pull factors are the primary drivers of capital flow after 2010's subsequent recovery [5]. In the literature, several empirical evidence shows that capital flows are impacted by domestic factors, such as opening-up policies in emerging countries, domestic economic growth, asset return indicators, country risk indicators, financial liberalization, macroeconomic policies, and reserve accumulation [6–8].

The G20 is a global forum, which brings together the world's advanced and emerging economies. Currently, there are 8 advanced economies (i.e., Australia, Canada, France, Germany, Italy, Japan, the U.K., and the U.S.), 11 emerging economies (Argentina, Brazil, China, India, Indonesia, Korea, Mexico, Russia, Saudi Arabia, South Africa, and Turkey), and the European Union. The development of the G20 plays a critical role in the world economy since the G20 accounts for eighty-five percent of the world GDP and two-thirds of the world population [9]. The G20 heads of

government have periodically conferred at summits to discuss policy issues about the promotion of international financial stability.

According to G20 Guiding Principles for Investment Policymaking, the G20 countries agree to move towards better openness for global capital flows and facilitate investments that occur in a nation with weak growth [10, 11]. However, in the 2008 global financial crisis and the 2010 recovery, the shocks of capital flows have highly heterogeneous effects across countries [5]. Global leaders are seeking cooperative solutions to prevent further crises. Also, the G20 summit works on macroprudential policy frameworks, including tools (i.e., capital controls and foreign currency reserves) to mitigate the impact of excessive capital flows [12]. In the future, efficient capital flow management, from a practical economic and financial risk management perspective, will facilitate the stability of capital flows between advanced and emerging nations.

This paper contributes some new empirical evidence for solving the complexity of problems in the fields of global capital flow management and international monetary policies. This study applies panel vector autoregression (Panel-VAR) to capture the linear interdependencies among stock traded/GDP, real-world GDP growth, and FDI inflows. Next, further study examines how capital flows are associated with pull and push factors by using the system GMM methodology and fixed-effect regressions. First, this study hypothesizes that international capital flows are significantly impacted by the liquidity of the stock market because domestic financial developments can help absorb capital flows and deal with their volatility. Second, push factors also play important roles to drive capital flow. For example, the growth of the global economy significantly impacts the size and composition of capital flows across G20 countries; the capital inflows from advanced economies to emerging economies are greatly affected by U.S. monetary policy and the supply of U.S. dollars; the volatility of crude oil price has some spillover effects on capital flows. Third, this study controls for foreign currency reserves and capital restrictions, because government intervention on capital accounts should have a noticeable impact on capital flows, especially in emerging countries.

2. Literature Review

After the 1990s, some studies support the neoclassical growth model, in which capital flows from richer countries with the relatively high capital-to-labor ratio to poorer countries with relatively low rates [13]. However, since the Mexican currency crisis in 1994 and the Asian crisis in 1998, there was a substantial decrease in capital inflows to emerging countries. Thus, some studies have questioned the neoclassical economic framework and showed "Lucas Paradox" and "allocation puzzle," which indicate a lack of capital flow from rich to poor countries [14–17]. According to theoretical and empirical studies, the drivers of global capital flow can be directly determined by the push-pull framework: pull (or domestic) factors and push (or external) factors. Koepke [18] shows that push factors (i.e., U.S. interest rate and U.S. economic growth) significantly matter in most of the portfolio flows, while pull factors (i.e., domestic economic growth and country risk indicators) are most important for banking flows.

2.1. Theoretical Background about Global Capital Flows. In neoclassical growth theory, capital flow moves from rich countries with the relatively high capital-to-labor ratio to poor countries with relatively small ratios, due to the effect of diminishing returns of capital. However, the empirical evidence shows that the volume of capital flow to GDP in emerging countries is surprisingly low, which is the so-called Lucas Paradox. Lucas [17] proposes that the capital transmission from rich to poor countries can be influenced by two categories: (1) international market imperfections, such as sovereign risk and information asymmetry, and (2) huge differences in fundamentals, such as institutional quality, production capability, and technology. Some studies show that institutional quality, corporate governance, and quality of the financial systems are the primary causal variables explaining the Lucas Paradox [14, 19].

The allocation puzzle states that international capital flows do not move to countries with high growth and high investment rates but flow to low growth and low investment rates [16, 20]. Because Asia has experienced relatively great growth and high investment rates, it should have imported capital rather than exporting it. However, the reality is that high-growth and high-investment Asian countries tend to experience capital outflows. Some studies try to explain why such imbalances are originating in Asia and not in other emerging regions. Benhima [15] shows that Asia growth has not been compensated by matching the increase in human wealth, although it has increased a large capital accumulation. Thus, the asset demand of Asia is high relative to the asset supply, leading to capital outflows. Gourinchas and Jeanne [16] argue that emerging countries resist the real appreciation of their currency for export by the accumulation of foreign assets and restrictions on capital inflows. And then, emerging countries with higher growth in the tradable sector led to higher trade surpluses and so (as a matter of accounting) higher net capital outflows. In addition, excess net saving arises from excessive savings rather than an investment shortage among some emerging countries that run large current account surpluses.

Financial integration is not always Pareto improving. Phelan and Toda [21] show the effect of collateralized lending and securitization on global capital flows and welfare in a two-country equilibrium model with idiosyncratic investment risk. They suppose that the low-margin country (US) endogenously supplies more safe assets and enables more risk sharing. When the low-margin country receives capital inflows after financial integration (which is driven by the high-margin country's demand for relatively safe assets and low-margin country's ability to intermediate capital), the degree of risk sharing decreases through a lower interest rate, which can hurt welfare despite high investment levels.

Malmendier et al. [22] introduce the notion of experience-based learning into the international macromodels and show its potential to jointly explain some of the long-standing puzzles on capital flows and portfolio investment: home bias, fickleness, and retrenchment. Experience-based learning describes that agents overweight realizations observed during their lifetimes when forecasting output. Home bias means that investors choose to hold more equity wealth in their home countries even though they observe the global market yields because they are more confident about their knowledge of their own country than of a foreign country. Fickleness means the pattern of foreign capital outflows increasing during periods of domestic or global crises. Retrench indicates the pattern of domestic capital inflows increasing during periods of domestic or global crisis.

2.2. Push Factors of Global Capital Flows. First, in the 1990s, the falling interest rates in the U.S. attracted investors to high yields and high-growth economies in Asia and Latin America [3, 13, 23]. At the same time, most emerging countries appear to increase borrowing from the U.S. under the low interest rate. However, in the mid-1990s, a rise in interest rate by the tightening of monetary policy in the U.S. made an investment in Asia and Latin America relatively less attractive [13, 23]. Second, some empirical studies show that global risk aversion robustly impacts capital flows [1]. During the financial crisis, foreigners reduce their investment, and domestic agents also reduce capital outflows [5, 24, 25]. Third, mature economic growth, especially U.S. economic growth, positively drives global capital flows [1, 3, 4]. Fourth, Fed's unconventional monetary policy has a significant effect on international capital flows, including four main channels: portfolio channel, signaling channel, confidence channel, and liquidity channel. "The portfolio channel is that the Fed can reduce the supply of a specific security and investors with certain degree of preference for the asset will push its price up. The signaling channel works when announcements made by the Fed change expectations regarding the future stance of monetary policy. The confidence channel is that, in addition to the signals that announcements give about the future stance of monetary policy, they could give information about the economic performance. The liquidity channel operates through liquidity measures and purchases of MBS aimed at restoring the functioning of key markets and reducing the liquidity premium" [26].

Fifth, international portfolio diversification stimulates the U.S. and other investors to hold foreign securities. Some studies show that U.S. investors obtain significant benefits from international diversification [27]. Finally, international capital flows are positively associated with worldwide stock returns, consistent with positive feedback trading by international investors [28]. Market microstructure studies show that investors are more likely to invest in foreign assets in periods when the return on foreign assets is high and to sell when the return is low if domestic investors have a cumulative information advantage over foreign investors about their domestic market [29, 30]. When there are barriers to international capital flows and when the expectations of foreign investors are more extrapolative than those of domestic investors, unexpectedly high global stock returns lead to net equity inflows in small countries at the daily frequency [31].

2.3. Pull Factors of Global Capital Flows. First, domestic economic growth is an important driver of capital flows [3], but Kim [32] argues that domestic factors are relatively less important than push factors. Second, there are many studies showing how international capital flows interact with domestic market liquidity. Some studies show that financial development is positively associated with domestic firms investing abroad [33, 34]. Second, country risk indicators do influence capital flows. Kim and Wu [35] show that the better sovereign credit rating on foreign and local debt tends to attract capital flows. Third, Asiedu [36] shows that the foreign direct investments in Africa are promoted by large market size, natural resource endowments, great infrastructure, low inflation, good institutional quality, and good investment framework. Fourth, some studies argue that domestic institution quality has a substantial impact on international flows [19, 37, 38]. Finally, after the 1970s, increasingly emerging countries adopt open-up policies and offer special tax incentives and subsidies to attract foreign investments [39]. Also, some studies show that policy environments, such as liberalizing capital controls and policies of reserve currency, significantly impact capital flows [40–43].

2.4. Limitations of the Push-Pull Framework. A push-pull framework is an efficient approach to analyzing drivers of capital flows, but some factors do not fit into either push or pull categories, such as contagion effects and information asymmetries [18]. Since international capital markets are fictional, they are segmented by asymmetric information or home biases. Some studies show that asymmetric information, measured by geographic distance, is an important barrier to capital flows [44, 45]. Some studies show that push factors to developing economics can be a source of contagion, because a large capital shift from one or two countries (i.e., Mexico and Chile) may generate externalities for most Latin American countries [13]. Also, capital flows are driven by shifts in market sentiment or "hot" money [3]. The investor's speculative behaviors would result in volatile movements of capital flows between emerging and developed countries.

3. Hypotheses Development

This study supposes that both push and pull factors play significant roles in determining international capital flows. With economic globalization and political multipolarization, G20 countries include 8 advanced economies, European Union, and the 11 largest emerging economies. Under the complexity of global financial and political situations, each of the 20 largest economies plays an important role in global capital flows. The first hypothesis is that

domestic financial development should be an important determinant of output and investment, and it should have positive effects on outputs and investments. Well-developed capital markets that provide a rich pool of investment opportunities and plenty of exit options are likely to be found in large, stable, and growing economics [34]. On the contrary, the second hypothesis is that a well-developed financial market will attract more capital from foreign nations. According to the investment development path hypothesis [46], the capital inflows, in turn, promote economic and financial development as well.

In the complexity of globalization, all countries share global risks and liquidity problems. The third hypothesis is that the volatility of global economic conditions and oil prices significantly affect international capital flows. The final hypothesis is that financial policies in each county should affect global capital flows. Some studies show that macroprudential policies in Asian nations encourage reserve accumulation and maintain high levels of capital inflows [7, 47]. This study controls for interest rate, reserve accumulation growth, and capital restriction in our models.

4. Data and Methods

4.1. Data. This study explores how push and pull factors impact global capital flows in G20 countries. First, this study describes and analyzes G20 capital flows and the world's capital flows, which are collected from IMF-International Financial Statistics from 2000 to 2015 at an annual frequency, including foreign direct investment and foreign portfolio investment (FDI inwards, FDI outwards, and FPI inwards). This study also collects net FDI inwards/GDP, net FDI outwards/GDP, and net FPI inwards/GDP from World Development Indicators (WDI).

The international capital flows mainly include foreign direct investment (FDI) and foreign portfolio investment (FPI) and bank lending. The FDI represents establishing a long-term business in a foreign country, such as international mergers and acquisitions, and manufacturing transfers to countries with a cheap labor force. Moreover, the FPI typically indicates the short-term investment in financial assets, such as portfolio equity and portfolio debt. The empirical evidence shows that FDI is driven more by domestic financial development or economic growth and less by global financial fluctuations [34, 48]. By contrast, FPI is more driven by short-term changes than FDI. Specifically, portfolio equity is highly associated with fluctuations of the global stock market, and portfolio debt is more related to risks of currency markets [3, 6, 24, 49]. Moreover, some studies show that cross-border bank lending has been increasing rapidly, and the financial crisis significantly impacts bank lending [50, 51].

Second, the domestic financial development, the stock traded/GDP, and domestic credit by banks/GDP are collected from WDI as well. Third, the international capital flows are not only associated with domestic factors but also impacted by global factors. This study collects the price of WTI crude oil and the growth of world GDP from WDI. Finally, besides full-push factors, this study also controls for real interest rates, capital controls, and international currency reserves. Global capital flows have increased significantly in recent years, but the costs of capital flows are not eliminated, especially in some emerging countries. This study describes capital restrictions on inflows and outflows from 2002 to 2015 based on a new measure of capital controls developed by Fernández et al. [52]. The growth of reserve accumulation is collected from IMF-International Financial Statistics. The real interest rate from WDI is calculated as $(\mathrm{i} - P)/(1 + P)$, where I is the nominal lending interest rate and P is the inflation rate (as measured by the GDP deflator).

4.2. Methods. This study first explores relationships between pull-push factors and international capital flows by applying a VAR method, which treats all variables as endogenous. Moreover, the Granger causality test is applied to examine whether a time series factor is useful in predicting another, and forecast error variance decomposition (FEVD) is used to investigate the amount of information each factor contributes to the other factors in the VAR model. According to the Panel-VAR methodology developed by Love and Zicchino [53]; a first-order VAR model is proposed as follows:

$$Z_{i,t} = \alpha_0 + \alpha_1 Z_{i,t-1} + f_i + v_t + e_t, \tag{1}$$

where $i = 1, 2, \ldots, 19$ countries and $t = 1990, 1991, \ldots, 2015$ years. $Z_{i,t}$ is a three-variable vector (real-world GDP growth, either stock traded/GDP or domestic credit/GDP, and either FDI/GDP or FPI/GDP) from 2000 to 2015. This study transforms time series to become stationary by taking the first difference. f_i and v_t indicate unobserved individual effect and year effect. The order of the input variables is also following Love and Zicchino [53] assumptions: the variables that appear earlier in the VAR systems are more exogenous, and the ones that appear later are more endogenous. In the VAR models with three variables, this study assumes that the most endogenous variable is FDI or FPI inflows.

It also assumes real-world GDP growth as the most exogenous variable because world GDP growth is not explained by one country's capital flows and stock-market liquidity, especially for some small countries. Jansen and Stokman [54] show that countries that have comparatively intensive FDI relations also have more synchronized business cycles. Both larger inward and outward investment positions may make the domestic economy more susceptible to synchronized global business cycles. Moreover, this study assumes that financial development reaches a middle ground between world GDP and capital inflows because it is necessary for financial intermediation and the efficient allocation of investments within global economies. Financial development is measured by stock traded/GDP. Some studies show that stock-market development has positive effects on foreign investments, especially in low-income countries [55–57]. On the contrary, foreign investments also might promote or decrease stock-market development [58–60].

This study employs the system GMM methodology to explore how international capital flows are impacted by both pull and push factors and macroeconomic policies. Some

studies show that the system GMM is an efficient approach to testing long-run growth and the availability of macroeconomic data for large panels of countries [61–63]. Because the system GMM allows independent variables that are not strictly exogenous [64, 65], this study assumes the one lag of dependent variables (capital flows) as endogenous variables. Some studies find that the role of stock markets as a channel through which foreign capital flows could promote economic growth [66] and countries with well-developed stock markets gain significantly from capital flows [58]. In addition, cross-border financial flows can influence domestic credit through multiple channels [57]. Since international capital flows experience interaction with stock traded/GDP, the lags of stock traded/GDP and domestic credit/GDP are used as instruments for financial development. The basic specification is as follows:

$$\begin{aligned}\mathrm{FLOWS}_{i,t} = {} & \alpha_0 + \beta_1 \mathrm{FLOWS}_{i,t-1} + \beta_2 \mathrm{FD}_{i,t} + \beta_3 \mathrm{FD}_{i,t} \times \mathrm{CLASS} + \beta_4 \mathrm{OIL}_{i,t} + \beta_5 \mathrm{WD\_GDP}_{i,t} \\ & + \beta_6 \mathrm{RESERVE}_{i,t} + \beta_7 \mathrm{INT}_{i,t} + \beta_8 \mathrm{CONTROL}_{i,t} + \beta_9 \mathrm{CRISIS} + f_i + v_t + e_{i,t},\end{aligned} \tag{2}$$

where $i = 1, 2, \ldots, 19$ countries and $t = 1990, 1991, \ldots, 2005$ years. $\mathrm{FLOWS}_{i,t}$ is either the net FDI inwards/GDP, net FDI outwards/GDP, or net FPI inwards/GDP; $\mathrm{FLOWS}_{i,t-1}$ is the first lag of the dependent variable; $\mathrm{FD}_{i,t}$ is a measure of financial development (stock traded/GDP or domestic credit by banks/GDP); CLASS is country classification: developed countries (0) and emerging countries (1); $\mathrm{OIL}_{i,t}$ is WTI crude oil price; $\mathrm{WD\_GDP}_{i,t}$ is real-world GDP growth; $\mathrm{RESERVE}_{i,t}$ is foreign currency reserves/GDP; $\mathrm{INT}_{i,t}$ is real interest rate; $\mathrm{CONTROL}_{i,t}$ is the index of capital restrictions on inflows and outflows; CRISIS is dummy variable: 2007–2009 financial crisis (1) and other periods (0); v_i is the country-specific effect; v_t is a time-specific effect; and $e_{i,t}$ is the error term. The sample size is 19 countries (i) and covers 16 years (t) from 2000 to 2015. The European Union (EU) is excluded from G20 because the data of capital flows are unavailable in the IMF.

Financial market development should be positively associated with capital inflows because the better domestic financial markets would smoothly absorb enough sharp capital movements and reduce the risk of capital flows having adverse effects on the real economy [67]. A more liquid equity market is likely to attract foreign investors. Also, a reversal of capital flows becomes less likely if both local and foreign investors are confident that markets will remain liquid even under adverse conditions. In turn, Levine [68] shows that the effects of capital flows on economic growth occur through the channel of domestic financial intermediation. In other words, capital inflows promote the development of domestic financial markets and then have a positive influence on domestic growth. In addition, some studies show that surges in private capital inflows lead to domestic credit booms [69]. However, FDI inflows may also crowd out domestic credit if foreign capital costs are lower than costs of domestic bank lending [70]. This study also supposes that countries with too much domestic credit tend to have a lower level of capital inflows.

Advanced economies provide stable economic and political surroundings for domestic and foreign investors, but emerging countries are different. Equation (2) creates an interaction term by using a dummy variable (emerging countries (1) and developed countries (0)) to distinguish the effects of domestic financial development on capital flows between developed and emerging countries. Moreover, the robustness tests use two subsamples to avoid inappropriate pooling of developed and developing countries.

Push factors are the primary drivers of capital flows. In the previous studies, some studies show that the U.S. interest rate is the primary push factor [71]. Different from these studies, this study hypothesizes that world GDP growth and global oil price should be positively associated with capital flows. Some studies show the comovements between capital flows and business cycles [72]. Kim and Kim [73] argue that increased capital flows due to financial integration generate substantial impacts on business cycles. The increased financial linkages among global economies should have a significant impact on fluctuations in global external financing conditions. Financial contagion and the attendant financial crises may be one factor behind the increased business cycle comovement and affect capital flows among global markets. In addition, some studies show that commodity price cycles are associated with capital flow cycles and declines in both might lead to the financial crisis [74]. This study hypothesizes that the fluctuation of the oil price might affect international capital flows as well.

Finally, this study also controls for real interest rates, levels of capital controls in each country, and foreign exchange reserves. Interest rates are important to capital flows because capital flows move to countries with higher interest rates. However, compared with mature economies, emerging countries tend to use international reserves and capital controls to defend against currency crisis and intervene in the foreign exchange market to offset to some extent the effects on their economies of large capital flows [75–77]. Thus, the accumulation of foreign exchange reserves is usually employed by policymakers in emerging countries in an attempt to stem the tide of capital flows.

5. Results and Discussion

5.1. Descriptive Analysis. This section describes capital flows and push-pull factors. Figure 1 highlights each country's net capital inwards (or outwards) to the world's net capital inwards (or outwards). Combined U.S. and U.K. economies contribute the most, about 20% of the world's capital flows. Some other advanced economies, such as Germany, France, and Japan, have much more capital inwards of the world total than capital outwards. The rest of the countries appear

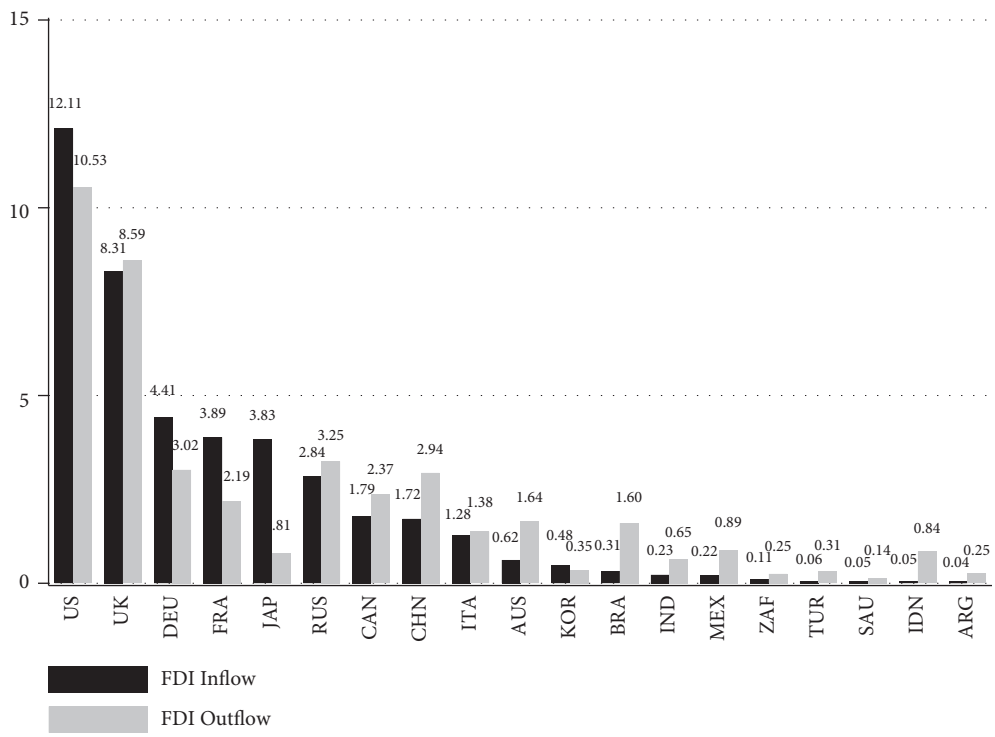

Figure 1: The volume of FDI inwards and outwards.

to have more capital outwards than capital inwards except South Korea. Besides developed countries, most emerging countries in G20, such as Russia, China, Brazil, Mexico, India, and Indonesia, contribute very high levels of FDI inwards and outwards. These results show that both advanced and emerging G20 members are important participants in the global capital flows. By contrast, Tables 1 and 2 show net capital inwards and outwards to domestic GDP. All developed countries have some higher capital outwards/GDP than capital inwards/GDP except Australia, while most emerging countries are just the opposite except South Korea and Russia.

Figure 2 compares FDI flows in high-income countries and middle and low-income countries. World Bank defines high-income economy (or developed country) as a country with a gross national income per capital over US$12,236 in 2016. The middle and low-income economy is a gross national income per capital less than US$12,236. The global capital flows are influenced by the changing international economic environment. For example, in 2007, the capital inflows and outflows significantly raised in both advanced and emerging countries, but the 2008–2009 global financial crisis triggered a global liquidity drought. In the high-income countries, the changes of FDI inflows were basically in agreement with the tendency of FDI outflows. From 2000 to 2014, FDI outflows were significantly higher than inflows, but outflows and inflows were the same in 2015. In the middle-low-income countries, capital inflows gradually descended after 2010, but capital outflows were rising year by year. So far, the volume of FDI inflows is still much larger than outflows in the middle-low-income countries. The weaker inflows and stronger outflows in emerging countries (or weaker outflows in developed countries) can be explained by the narrowing differential in economic growth between emerging and advanced economies.

This study also examines whether capital flows are driven by WTI crude oil prices. From Figure 2, from 2002 to 2007, both global capital investments and the oil price showed rising trends from 2002 to 2007, and they fell sharply in the 2008–2009 financial crisis. In the descriptive analysis, it is difficult to show the direct relationship between capital flows and oil prices since they are impacted by global economic development. Thus, the following multivariate analysis will further discuss the spillover effects between global capital investments and the oil price. Moreover, Figure 3 describes how capital flows between the U.S. and five regions. The global capital flows are mainly distributed between the U.S. and Europe, followed by the U.S. and Asia, the U.S. and Latin America, and the U.S. and Africa. In addition, the capital inflows are very close to outflows between the U.S. and Europe and Asia, while the U.S. outflows to Latin America and Africa are significantly larger than inflows from them.

Tables 1 and 2 show some important pull factors of capital flow: the liquidity of the domestic stock market and domestic credit. Based on the mean values in Table 1, the liquidity of stock markets is very high in some emerging countries, such as China, Korea, and Saudi Arabia, and domestic credit provided by banks is very strong in China, Korea, and South Africa. However, the financial development is low in some countries of Latin America, such as Argentina (14.15%) and Mexico (21.39%). By contrast, Table 2 shows that all developed countries have a relatively high level of financial liquidity in stock markets and banks, especially in U.S. markets (i.e., 223% of stock traded/GDP and 184% of domestic credit/GDP, respectively).

Table 1: Descriptive statistics in eleven emerging countries.

	Argentina	Brazil	China	India	Indonesia	Korea	Mexico	Russia	Saudi Arabia	South Africa	Turkey
FDI net inward/GDP	2.116	3.185	3.501	1.614	1.179	1.045	2.735	2.349	1.702	1.702	1.729
(std. dev.)	(0.760)	(1.016)	(0.731)	(0.820)	(1.654)	(0.419)	(0.654)	(1.237)	(1.482)	(1.482)	(1.000)
FDI net outward/GDP	0.308	0.747	0.780	0.638	0.971	1.586	0.745	2.543	0.455	0.458	0.336
(std. dev.)	(0.351)	(0.745)	(0.356)	(0.528)	(0.278)	(0.734)	(0.509)	(0.962)	(0.377)	(1.247)	(0.213)
FPI net inward/GDP	−0.020	0.603	0.054	0.015	0.001	0.001	0.009	−0.001	0.001	0.154	1.885
(std. dev.)	(0.187)	(0.605)	(0.037)	(0.016)	(0.001)	(0.001)	(0.038)	(0.013)	(0.001)	(0.230)	(2.474)
Stock traded/GDP	1.371	26.042	92.364	48.372	10.817	118.611	8.111	30.187	112.128	57.309	43.615
(std. dev.)	(1.004)	(11.731)	(86.097)	(24.332)	(4.244)	(37.275)	(2.660)	(26.417)	(108.956)	(17.608)	(9.250)
Domestic credit/GDP	14.151	45.060	121.292	43.309	27.740	125.911	21.393	35.316	36.395	140.507	38.398
(std. dev.)	(3.691)	(15.163)	(13.543)	(9.477)	(5.847)	(19.121)	(5.980)	(13.837)	(7.999)	(13.753)	(22.759)
Int'l Reserve/GDP	0.098	0.112	0.342	0.156	0.129	0.238	0.099	0.218	0.599	0.090	0.105
(std. dev.)	(0.037)	(0.043)	(0.106)	(0.035)	(0.026)	(0.036)	(0.031)	(0.077)	(0.369)	(0.030)	(0.012)
Real interest rate	−0.062	36.639	2.104	5.438	4.255	3.782	2.032	−1.586	N/A	4.304	N/A
(std. dev.)	(10.846)	(9.323)	(2.575)	(2.657)	(4.610)	(1.506)	(2.219)	(6.387)	N/A	(1.588)	N/A
Inflow control	0.546	0.457	0.992	0.907	0.692	0.221	0.532	0.596	0.739	0.371	0.339
(std. dev.)	(0.248)	(0.315)	(0.026)	(0.018)	(0.047)	(0.125)	(0.031)	(0.123)	(0.068)	(0.025)	(0.094)
Outflow control	0.739	0.575	0.985	0.975	0.589	0.282	0.550	0.560	0.553	0.853	0.450
(std. dev.)	(0.222)	(0.140)	(0.036)	(0.042)	(0.062)	(0.267)	(0.100)	(0.269)	(0.013)	(0.074)	(0.181)

Note. The mean value of each variable is shown. Standard deviation is provided within parentheses. The capital flows include net FDI inwards/GDP, net FDI outwards/GDP, and net FPI inwards/GDP. The financial development is measured by stock traded/GDP and domestic credit/GDP. The International Reserve Growth measures macroeconomic policies of reserve accumulation. The real interest rates are collected from WDI. This study also describes capital restrictions on inflows and outflows from 2002 to 2015 based on a new measure of capital control [52].

Table 2: Descriptive statistics in eight developed countries.

	Australia	Canada	France	Germany	Italy	Japan	U.K.	U.S.
FDI net inward/GDP	3.322	3.518	2.139	2.449	0.952	0.183	4.355	1.711
(std. dev.)	(2.186)	(2.416)	(1.169)	(2.913)	(0.604)	(0.164)	(3.271)	(0.639)
FDI net outward/GDP	1.203	3.827	3.921	2.974	1.556	1.610	4.648	2.144
(std. dev.)	(2.020)	(1.247)	(2.858)	(1.306)	(0.993)	(0.794)	(5.776)	(0.726)
FPI net inward/GDP	0.796	0.603	1.248	0.537	0.272	0.008	2.419	0.898
(std. dev.)	(1.225)	(0.949)	(1.572)	(1.426)	(0.733)	(0.011)	(4.888)	(0.801)
Stock traded/GDP	81.054	79.924	62.792	55.308	55.900	84.755	94.353	222.965
(std. dev.)	(28.902)	(16.474)	(20.053)	(24.358)	(21.806)	(34.001)	(26.166)	(51.792)
Domestic credit/GDP	113.899	152.359	87.963	95.419	80.539	181.386	153.328	184.085
(std. dev.)	(15.505)	(31.089)	(8.896)	(12.052)	(12.243)	(9.519)	(25.874)	(12.323)
Int'l Reserve/GDP	0.041	0.038	0.020	0.020	0.020	0.184	0.024	0.007
(std. dev.)	(0.013)	(0.007)	(0.004)	(0.005)	(0.005)	(0.055)	(0.007)	(0.002)
Real interest rate	3.829	1.985	4.939	4.662	3.580	2.425	0.953	2.889
(std. dev.)	(1.651)	(1.498)	(0.940)	(2.325)	(0.618)	(1.328)	(1.924)	(1.634)
Inflow control	0.278	0.100	0.003	0.064	0.001	0.001	0.007	0.100
(std. dev.)	(0.037)	(0.001)	(0.013)	(0.049)	(0.001)	(0.001)	(0.026)	(0.001)
Outflow control	0.314	0.001	0.089	0.257	0.050	0.001	0.001	0.182
(std. dev.)	(0.146)	(0.001)	(0.056)	(0.198)	(0.001)	(0.001)	(0.001)	(0.024)

Foreign exchange reserve is a critical macroprudential policy to manage capital flows and exchange rates. Table 2 shows that all developed countries have a relatively lower foreign exchange reserve/GDP, except for Japan (0.184). Table 1 shows that some emerging countries also have much more international reserves, especially in Saudi Arabia (0.599), China (0.342), Korea (0.238), and Russia (0.218). Moreover, every country has some restrictions on capital flows, but the average capital controls on both inflow and outflows are much higher in emerging countries than in developed countries. In the developed countries, Australia has significant capital controls on both inflows and outflows, and Germany and the U.S. limit capital outflows.

Finally, the correlation matrix in Table 3 detects multicollinearity among some of the independent variables. This study finds a high correlation coefficient between world GDP growth and oil price (0.715) and the stock traded/GDP and domestic credit/GDP (0.598). In the following

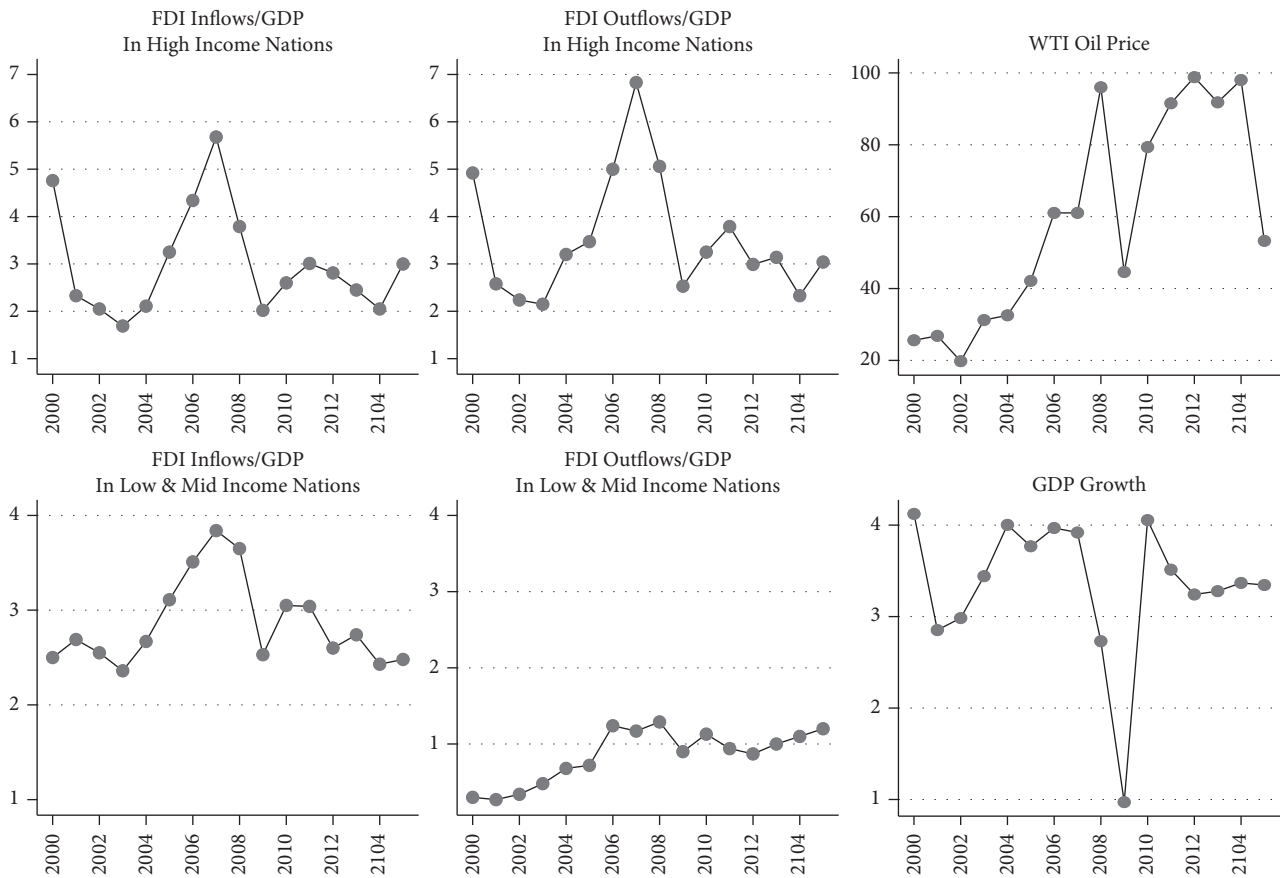

Figure 2: World trends. Source: FDI inflows/GDP and FDI outflows/GDP in high-, mid-, and low-income nations are available in World Development Indicators (WDI). The WTI oil price and real GDP growth are collected from DataStream.

regression analysis, this study estimates (1) world GDP growth and crude oil price and (2) stock traded/GDP and domestic credit/GDP in separate models.

5.2. Granger Causality and FEVD. This section examines the Granger causality between FDI/FPI inwards/GDP, financial development (stock traded/GDP and domestic credit/GDP), and world GDP. Panels A and B in Table 4 show that the inflows of FDI and FPI are significantly affected by shocks of stock traded and world GDP growth. However, Panels C and D show FDI inflows are insignificantly impacted by shocks of domestic credit.

The variance decompositions for the VAR model, presented in Table 5, show how much of the forecast error for each variable can be influenced by exogenous shocks to the other variables. Panel A in Table 5 shows that the variation of FDI inflows is affected by 73.3% of itself after 5 years, 16.5% shocks of world GDP growth, and 10.3% shocks of stock traded/GDP. Panel B shows that the variation of FPI inflows is impacted by 65.2% of itself, 27.2% shocks of world GDP growth, and 7.6% shocks of stock trading. However, Panels C and D show that the shock of domestic credit/GDP has a minor effect on FDI/FPI inflows. In addition, the variations of world GDP growth, the stock traded/GDP, and domestic credit/GDP are most affected by themselves (over 90%). Thus, the VAR models show that international capital flows are significantly affected by the world business cycle and domestic stock-market liquidity. However, world business cycles have a stronger influence on capital flows than domestic financial development.

5.3. Results of Regressions. Table 6 shows the effects of pull-push drivers on international capital flows in G20 countries from 2000 to 2015. Table 7 examines capital flows in 8 emerging countries (i.e., Australia, Canada, France, Germany, Italy, Japan, the U.S., and the U.K.) and Table 8 examines capital flows in 11 emerging countries (i.e., Argentina, Brazil, China, India, Indonesia, Korea, Mexico, Russia, Saudi Arabia, South Africa, and Turkey), respectively.

Domestic financial development can help absorb capital flows and deal with their volatility, so this study proposes that the liquidity provided by stock markets and banks will significantly impact capital flows. Table 6 shows that the liquidity of stock markets is positively associated with FDI and FPI flows. In the literature, some studies show that the liquidity of stock markets positively influences capital inflows [28, 29]. It seems plausible that foreign investors are attracted by liquid stock markets. The high liquidity of stock markets enhances investors' capacity to materialize potential gains quickly and at low costs. Alternatively, countries with

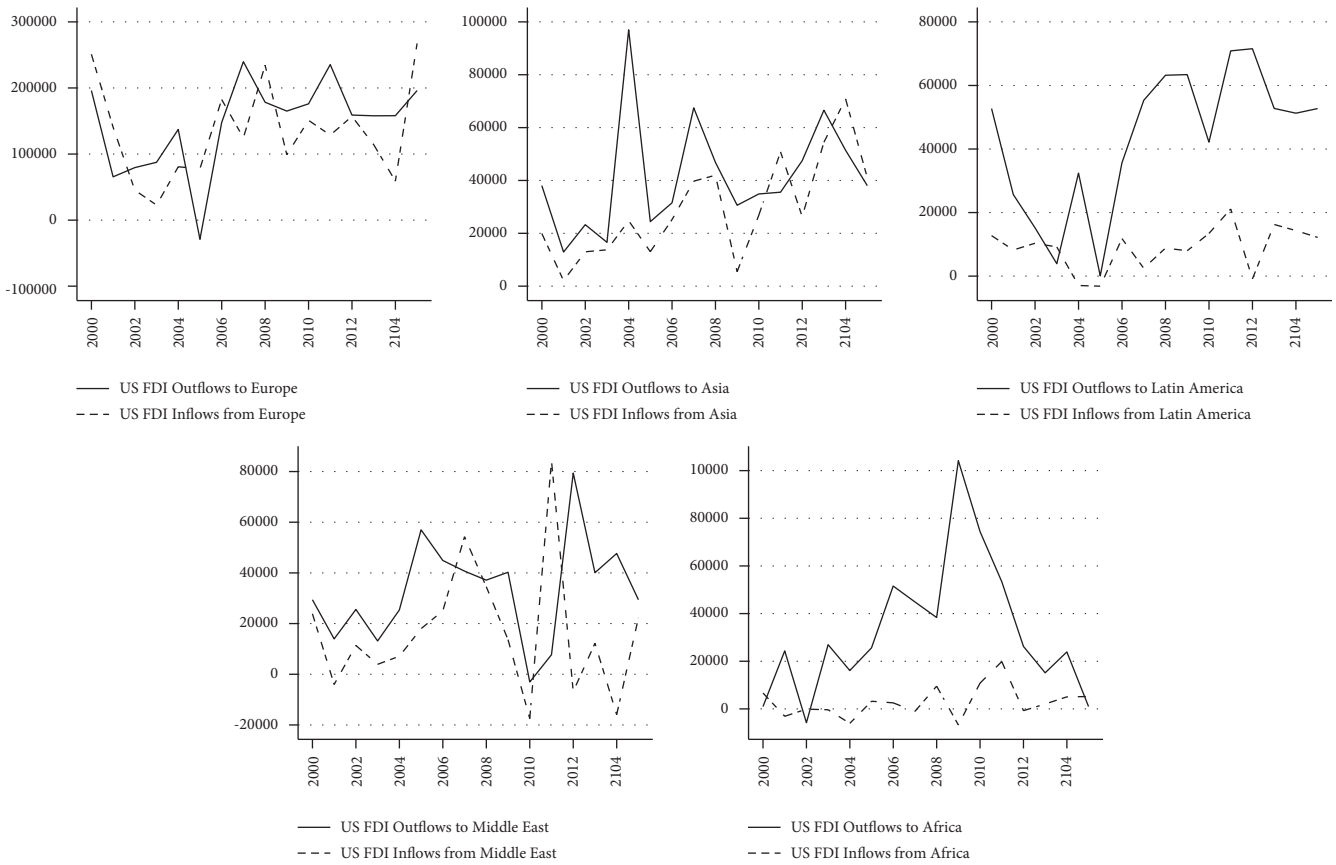

Figure 3: Capital flows between the U.S. and five regions. Sources: The U.S. FDI inflow and outflows are collected from IMF World Economic Outlook.

Table 3: Correlation matrix.

	Stock traded/GDP	Domestic credit/GDP	World GDP growth	Crude oil	Real interest rate	Reserve accumulation growth	Capital restriction
Stock traded/GDP	1.000						
Domestic credit/GDP	0.598	1.000					
World GDP growth	0.045	−0.016	1.000				
Crude oil	0.042	0.003	0.715	1.000			
Real interest rate	−0.131	−0.075	−0.077	−0.072	1.000		
Reserve accumulation growth	−0.054	−0.112	0.128	−0.040	0.046	1.000	
Capital restriction	−0.235	−0.258	0.009	−0.067	−0.269	−0.090	1.000

high liquidity in stock markets are also likely to invest abroad to diversify portfolio risks and seek higher-return investments.

Moreover, columns (1) and (7) of Table 6 show that the interaction effects terms (stock traded/GDP ∗ country classification) have significant effects on FDI outflows and FPI inflows, suggesting effects of stock-market liquidity on capital flows work differently between advanced and emerging economies. Tables 7 and 8 split the sample into advanced and emerging countries. These results show that there are some positive effects between stock-market liquidity and capital flows in developed economies in Table 7. In contrast, columns (9) and (10) in Table 8 show that stock-market liquidity is only positively related to capital outflows, suggesting emerging countries tend to increase capital outflows when stock markets are well-developed. Domestic financial development in emerging countries has no significant spillover effects on capital inflows.

Under financial integration, local banks can seek funding from foreign portfolio investors, foreign direct investors, interbank markets, money markets, and international bond issues. Thus, some studies show that domestic credit growth is affected by international capital flows [57, 78]. Some empirical evidence shows that FDI flows flood into domestic banks and markets when domestic credit grows slowly. However, if foreign firms can borrow heavily from local banks, domestic credit may crowd out foreign capital inflows [79]. However, this study does not find a significant relationship between domestic credit and capital flows in Table 6.

Table 4: Granger causality.

	CHI^2/DF	*P* value		CHI^2/DF	*P* value
Panel A			Panel C		
World GDP growth⟶stock traded/GDP	0.275/1	0.600	**World GDP growth⟶domestic credit/GDP**	**12.101/2**	**0.002**
World GDP growth⟶FDI inflow/GDP	**3.974/1**	**0.046**	**World GDP growth⟶FDI inflow/GDP**	**6.901/2**	**0.032**
Stock traded/GDP⟶world GDP growth	0.410/1	0.522	**Domestic credit/GDP⟶world GDP growth**	**6.633/2**	**0.036**
Stock traded/GDP⟶FDI inflow/GDP	**4.952/1**	**0.026**	Domestic credit/GDP⟶FDI inflow/GDP	0.815/2	0.665
FDI inflow/GDP⟶world GDP growth	1.613/1	0.204	FDI inflow/GDP⟶world GDP growth	0.795/2	0.672
FDI inflow/GDP⟶stock traded/GDP	2.073/1	0.150	FDI inflow/GDP⟶domestic credit/GDP	0.381/2	0.827
Panel B			Panel D		
World GDP growth⟶stock traded/GDP	3.141/3	0.370	**World GDP growth⟶domestic credit/GDP**	**11.330/2**	**0.003**
World GDP growth⟶FPI inflow/GDP	**9.182/3**	**0.027**	**World GDP growth⟶FPI inflow/GDP**	**7.279/2**	**0.026**
Stock traded/GDP⟶world GDP growth	**42.61/3**	**0.001**	**Domestic credit/GDP⟶world GDP growth**	**6.552/2**	**0.038**
Stock traded/GDP⟶FPI inflow/GDP	**8.186/3**	**0.042**	Domestic credit/GDP⟶FPI inflow/GDP	0.058/2	0.971
FPI inflow/GDP⟶world GDP growth	4.654/3	0.199	**FPI inflow/GDP⟶world GDP growth**	**13.127/2**	**0.001**
FPI inflow/GDP⟶stock traded/GDP	**13.731/3**	**0.003**	FPI inflow/GDP⟶domestic credit/GDP	1.352/2	0.508

Note. The Granger causality is a statistical hypothesis for exploring whether each time series can forecast another. The model in Panel A examines a large number of hypotheses in the three-variable vector: world GDP growth, the stock traded/GDP, and FDI inwards/GDP. Panel B tests a VAR model in a three-variable vector: world GDP growth, the stock traded/GDP, and FPI inwards/GDP. Panel C tests a VAR model in a three-variable vector: world GDP growth, domestic credit/GDP, and FDI inwards/GDP. Panel D tests a VAR model in a three-variable vector: world GDP growth, domestic credit/GDP, and FDI inwards/GDP. Based on the Bayesian information criterion (BIC), the appropriate one lag is selected in Panel A, three lags in Panel B, and two lags in Panels C and D.

Table 5: FEVD.

	Steps	World GDP growth	Stock traded/GDP	FDI inflow/GDP		Steps	World GDP growth	Domestic credit/GDP	FDI inflow/GDP
		Panel A					Panel C		
World GDP growth	1	1.000	0.001	0.001	World GDP growth	1	1.000	0.001	0.001
	3	0.976	0.013	0.011		3	0.953	0.037	0.010
	5	**0.972**	**0.015**	**0.013**		5	**0.927**	**0.063**	**0.010**
Stock traded/GDP	1	0.022	0.978	0.001	Domestic credit/GDP	1	0.024	0.976	0.001
	3	0.036	0.955	0.009		3	0.091	0.908	0.001
	5	**0.037**	**0.950**	**0.013**		5	**0.093**	**0.903**	**0.004**
FDI inflow/GDP	1	0.047	0.005	0.948	FDI inflow/GDP	1	0.039	0.002	0.958
	3	0.158	0.071	0.771		3	0.159	0.003	0.838
	5	**0.165**	**0.103**	**0.733**		5	**0.173**	**0.003**	**0.824**
		Panel B					Panel D		
World GDP growth	1	1.000	0.001	0.001	World GDP growth	1	1.000	0.001	0.001
	3	0.855	0.129	0.015		3	0.919	0.043	0.038
	5	**0.878**	**0.109**	**0.013**		5	**0.897**	**0.064**	**0.040**
Stock traded/GDP	1	0.001	1.000	0.001	Domestic credit/GDP	1	0.028	0.972	0.001
	3	0.012	0.924	0.064		3	0.070	0.929	0.001
	5	**0.030**	**0.902**	**0.068**		5	**0.063**	**0.936**	**0.001**
FPI inflow/GDP	1	0.029	0.060	0.912	FPI inflow/GDP	1	0.002	0.010	0.987
	3	0.160	0.066	0.774		3	0.029	0.010	0.961
	5	**0.272**	**0.076**	**0.652**		5	**0.032**	**0.011**	**0.957**

Note. The FEVD investigates how much the forecast error variance of each variable can be influenced by exogenous shocks to the other variables. This study specifies the maximum steps or periods are five.

Push factors are also important drivers of capital flows. Columns (1), (2), (4), and (5) in Table 6 show that world GDP growth significantly impacts international capital flows. Along with the good development of the global economy, all countries tend to expand their international capital flows. Forbes and Warnock [1] explain capital flow waves: surges, stops, flight, and retrenchment. They find that many investments moved from developed countries to emerging countries since the GDP and global stock markets increased rapidly in some emerging countries from 2000 to 2007. After 2010, global economic development slowed down and the U.S. dollar became stronger while investments flowed back to advanced economies. At present, global FDI is expected to decline due to the fragility of the global economy and the president's weakness of aggregate demand. This study controls for the 2007–2009 financial crisis. The negative relationship between the financial crisis and capital flows suggests that all countries tend to reduce capital inflows and outflows during the financial crisis.

Fluctuations in the oil price also affect foreign capital flows. The G20 members, such as Russia, Saudi Arabia, Canada, and Latin America, are the main oil-exporting

Table 6: Results of system GMM in G20 countries.

Variables	(1) FDI inwards	(2) FDI inwards	(3) FDI inwards	(4) FDI outwards	(5) FDI outwards	(6) FDI outwards	(7) FPI inwards	(8) FPI inwards	(9) FPI inwards
A lagged dependent variable	0.426***	0.383***	0.392***	0.496***	0.448***	0.386***	0.389**	0.326***	0.390**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.025)	(0.001)	(0.022)
Stock traded/GDP	0.081*	0.204*		0.399*	0.600*		0.251**	0.142**	
	(0.064)	(0.075)		(0.072)	(0.076)		(0.027)	(0.026)	
Stock traded* classification	−0.098*			−0.359			−0.420***		
	(0.072)			(0.127)			(0.003)		
Domestic credit			0.073			−0.096			0.035
			(0.804)			(0.647)			(0.874)
Domestic credit* classification			−0.355			−0.245			−0.289**
			(0.258)			(0.241)			(0.040)
World GDP growth	0.128**	0.119**		0.146*	0.155*		−0.042	0.059*	
	(0.019)	(0.042)		(0.067)	(0.060)		(0.227)	(0.051)	
Crude oil			0.023**			0.024			−0.014
			(0.022)			(0.123)			(0.411)
Real interest rate	0.010*	0.021*	0.015*	−0.005		−0.001	0.005		0.010
	(0.052)	(0.036)	(0.085)	(0.703)		(0.958)	(0.619)		(0.205)
Reserve accumulation growth	0.535			−0.216			0.478		
	(0.353)			(0.693)			(0.346)		
Crisis 2007–2009 dummy	−0.508*	−0.209*	−0.376*	−0.444	−0.412	−0.490	0.035	−0.172	0.008
	(0.062)	(0.066)	(0.060)	(0.231)	(0.191)	(0.104)	(0.874)	(0.338)	(0.963)
Capital restriction			0.866			−1.305**			−0.422
			(0.182)			(0.028)			(0.321)
Observations	282	282	278	278	278	274	271	271	267
Number of countries	19	19	19	19	19	19	19	19	19
Sargan (P value)	0.318	0.522	0.721	0.335	0.553	0.344	0.514	0.495	0.333
Arellano-Bond (2) (P value)	0.503	0.325	0.381	0.666	0.625	0.368	0.318	0.332	0.494

Note. The system GMM regressions are used to examine all hypotheses. The dependent variables are FDI inwards/GDP, FDI outwards/GDP, and FPI inwards/GDP. The pull factors are measured by stock traded/GDP and domestic credit by banks/GDP. The push factor is measured by world GDP growth and the price of WTI crude oil. The models control for a lagged dependent variable, the stock traded/GDP, and domestic credit provided by banks as endogenous variables. The rest of independent variables are exogenous. The null hypothesis of Sargan test is that the instruments are valid instruments. The null hypothesis of Arellano-Bond test is no autocorrelation in the second order. Robust P value is provided within parentheses: $^{***}P < 0.01$, $^{**}P < 0.05$, and $^{*}P < 0.1$.

Table 7: Regression analysis in eight developed countries.

Variables	(1) FDI inwards	(2) FDI inwards	(3) FDI outwards	(4) FDI outwards	(5) FPI inwards	(6) FPI inwards
Stock traded/GDP	**0.068****	**1.202***	**0.065***	**1.024***	**0.171***	**0.255***
	(0.016)	**(0.099)**	**(0.053)**	**(0.066)**	**(0.075)**	**(0.057)**
World GDP growth	**0.246****		**0.332****		-0.204	
	(0.032)		**(0.020)**		(0.517)	
Crude oil		−0.001		−0.009		−0.009
		(0.877)		(0.335)		(0.279)
Real interest rate	**0.214****	**0.477*****	0.193	0.437	0.032	0.142
	(0.040)	**(0.001)**	(0.432)	(0.310)	(0.683)	(0.341)
Reserve accumulation growth	−1.582		−0.358		0.132	
	(0.111)		(0.769)		(0.858)	
Capital restriction		−8.979		−6.530		0.137
		(0.266)		(0.117)		(0.988)
Crisis 2007–2009 dummy	**−0.876***	−0.249	**−1.519****	−0.301	−0.198	−0.024
	(0.075)	(0.633)	**(0.013)**	(0.630)	(0.588)	(0.967)
Constant	1.286	0.275	1.912*	0.605	1.026	0.701
	(0.161)	(0.838)	(0.093)	(0.682)	(0.135)	(0.637)
Observations	117	112	117	112	117	112
Number of countries	8	8	8	8	8	8
R^2	0.140	0.201	0.141	0.153	0.163	0.135

Note. The fixed-effect regressions are used to examine all hypotheses. The dependent variables are FDI inwards/GDP, FDI outwards/GDP, and FPI inwards/GDP, respectively. The independent variables include stock traded/GDP, world GDP growth, and WTI oil price. Also, the models control for real interest rate, foreign exchange reserves, capital account restriction, and the 2007–2009 financial crisis (dummy variable). Table 8 examines capital flows in 8 developed countries (i.e., Australia, Canada, France, Germany, Italy, Japan, the U.S., and the U.K.). Robust P value is provided within parentheses: $^{***}P < 0.01$, $^{**}P < 0.05$, and $^{*}P < 0.1$.

Table 8: Regression analysis in eleven emerging countries.

Variables	(1) FDI inwards	(2) FDI inwards	(3) FDI outwards	(4) FDI outwards	(5) FPI inwards	(6) FPI inwards
Stock traded/GDP	−0.294	−0.052	**0.616*****	**0.529****	0.058	0.121
	(0.261)	(0.909)	**(0.001)**	**(0.048)**	(0.335)	(0.244)
World GDP growth	**0.103****		**0.112****		−0.009	
	(0.029)		(0.020)		(0.585)	
Crude oil		**0.018***		**0.010*****		−0.001
		(0.064)		**(0.001)**		(0.395)
Real interest rate	**0.034****	**0.007***	0.006	0.001	−0.004	−0.005
	(0.030)	**(0.054)**	(0.581)	(0.937)	(0.288)	(0.342)
Reserve accumulation growth	−0.556		−0.278		**0.275*****	
	(0.189)		(0.351)		**(0.006)**	
Capital restriction		**0.678***		**−1.074*****		**0.410****
		(0.080)		**(0.009)**		**(0.014)**
Crisis 2007–2009 dummy	**−0.667*****	−0.286	−0.207	−0.090	−0.003	−0.030
	(0.006)	(0.281)	(0.227)	(0.558)	(0.961)	(0.625)
Constant	2.746***	1.512**	0.542**	0.733	0.089	−0.097
	(0.001)	(0.040)	(0.021)	(0.125)	(0.243)	(0.559)
Observations	165	165	162	162	154	154
Number of countries	11	11	12	13	14	15
R^2	0.106	0.173	0.168	0.333	0.189	0.105

countries. Columns (2) and (4) in Table 8 show that the oil price has a positive effect on capital flows in emerging countries. For the Russian economy, in particular, some studies show that the oil and gas sector accounts for 30% of FDI [80]. FDI in Russia has been adversely affected by the fall of the oil price since June 2014. However, fluctuations in the oil price have insignificant effects on international capital flows in developed countries.

This study also controls for real interest rate, capital control, and growth of reserve accumulation, which play a major role to avoid excessive imbalances in central banks and intervene in foreign exchange rates, thus affecting capital flows. The high domestic interest rate leads to capital inflows in columns (1) and (2) in Tables 6–8. Moreover, compared with developed countries, emerging countries have higher capital reserves and capital controls. Since most emerging countries have inefficient capital markets and low levels of capital development, governments need foreign exchange reserves to help them stabilize their currencies. The results indicate reserve accumulation growth might increase capital inflows and slightly decrease outflows. Table 7 shows that capital controls and growth of reserve accumulation have no significant influence on capital flows in developed countries. Table 8 shows that reserve accumulation growth is positively related to FPI inwards in developed countries. In addition, columns (2), (4), and (12) show the positive relationship between capital restriction and FDI/FPI inwards and negative linkage between capital restriction and FDI outwards, indicating emerging countries with more stringent capital restriction tend to increase capital inflows and reduce capital outflows.

6. Conclusions and Implications

With the rise of emerging countries, regional cooperative organizations, and multilateral activities, international capital flows do not simply move from rich (advanced) with the relatively high capital-to-labor ratio to the poor (emerging) with relatively low rates. IMF's report on foreign direct investment in emerging market countries in 2003 shows that some certain general factors consistently determine which emerging countries attract the most FDI. First, the market size and growth prospects of the host country significantly affect investment location because FDI emerging countries are increasingly being undertaken to serve domestic demand rather than to tap cheap labor. Second, the wage-adjusted productivity of labor and availability of infrastructure are still the main factors that influence the FDI. Third, legal protection for investors and institution quality are especially important factors when investors decide on whether to enter a new country.

This study contributes to the existing body of knowledge in an attempt to explore some drivers of international capital flows, such as (1) domestic financial development (i.e., domestic stock traded and domestic credit provided by banks), (2) some external factors (i.e., world GDP growth and crude oil fluctuation), and (3) some other control variables, such as capital restrictions and reserve accumulation growth. The domestic development of the stock market has a significant spillover effect on international capital inflows and outflows, especially in developed countries. In emerging countries, capital inflows and outflows are highly influenced by levels of capital openness and governance policies, while this study still finds that emerging countries with well-developed stock markets significantly increase capital outflows.

This study shows that global capital flows have been impacted by the changes in the global economy, the world's oil price, and the U.S. interest rate. For example, the Brazilian economic recession of 2014–2017 is mainly impacted by slowing global economic growth and falling commodity prices weighing on FDI flows to emerging countries. According to a report from the 2016 ECB Economic Bulletin

[81], the development of oil producers such as state-owned Petrobras accounts for 10% of total Brazilian investments and almost 2% of GDP. The firm had to reduce investments by 33% to adjust to the crash of oil prices from 2014 to 2015. In addition, global investors suddenly sold off large shares of securities in emerging markets because the U.S. announced it would wind down asset purchases (the "taper tantrum") in 2013. After December 2015, the U.S. Federal Reserve began to raise interest rates. Brazil's economy suffered capital outflows and entailed a surge in interest payments on public borrowing according.

Capital account liberalization is an ultimate objective in the G7 countries, but many developing nations in G20 need to liberalize gradually. History has taught us that the excesses of capital inflows into Mexico in 1994, Thailand in 1996–1997, and Russia in 1998 became the roots of the domestic financial crisis and quickly spread to a global currency and equity markets. At the same time, the falling interest rates in the U.S. attracted investors due to high yields and high-growth economies in Asia and Latin America. Although some emerging countries have integrated into the global capital markets, for a long time, they will still need capital controls and macroprudential policies because their macroeconomic and domestic financial systems are not sufficiently strong to deal with the high volatility of capital flows. However, in the current global capital markets, capital controls and macroprudential policies in emerging countries also can incur the imbalance of capital flows between emerging and advanced economies. Thus, both macroprudential measures and capital flow management measures are key topics at the G20 summit.

Adams-Kane and Lopez [82] show that strong economic and financial fundamentals in place and an effective supervisory and regulatory policy framework are two primary aspects to attract capital from different types of investors. "However, the main policy challenge is to design a set of standards appropriate for a specific country's stage of economic development that will promote capital inflows while preserving the resilience of its banking and financial system" ([82], p. 2). "The G20 is an essential platform to discuss and design such cross-border policy frameworks and standards. The diversity of its members, with very different levels of economic and financial development, ensures the representation of a broad range of views" ([82], p. 3). Adams-Kane and Lopez [82] argue that the G20 summit can seek further global collaboration on the following four priorities: an adaptable and flexible global framework, the generalization of international standards and best practices, a strong global data depository, and regulatory and monitoring cooperation.

Data Availability

The data used to support the findings of this study are included in the article. The sample is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Authors' Contributions

The authors contributed equally to this study.

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