Complexity

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Research Article

Compliance Risk Assessment in the Banking Sector: Application of a Novel Pairwise Comparison-Based PRISM Method

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Up-to-date compliance management uses a risk-based approach based on international standards. In addition to techniques and practices, implementing compliance measures is determined by principles and culture. Compliance risk assessment is an evolving field in theory and practice. Compliance risk management is complex and highly dependent on the decisions of experts. This article presents a new compliance risk assessment method based on a commercial banking case study. In the study, the Guilford method is used to extend the Partial Risk Map (PRISM) assessment technique, and the steps of the proposed pairwise comparison-based PRISM method are described in detail. Since risk assessment is critical to the operation and development of compliance management systems, the proposed risk assessment method involves testing individual evaluations' consistency and the results' robustness. The best-fitting and outlier experts can be identified based on testing the impact of individual expert rankings on the aggregated ranking. The main finding is that top partial risks can be identified by applying the proposed pairwise comparison-based PRISM technique; therefore, possible optimal risk mitigation strategies and measures can be designed.

1. Introduction

Compliance management is an organizational function responsible for fulfilling legal, regulatory, industrial, and other obligations. The compliance management function is usually independent and reports to top-level executives and the board [1]. Preferably, one person is formally responsible for operating the compliance management system (CMS). At the same time, the responsible department has a thorough knowledge and know-how of organizational operations, processes, and procedures. The maturity and scope of a CMS, the budget, and the workforce allocated demonstrate leadership's commitment to a compliant and trustworthy way of running the business.

The scope of compliance has recently expanded, and the approach of integrating operational and compliance risk, one of the critical categories of banking risks, is becoming widespread [2, 3]. Compliance risk management involves understanding and quantifying risk tolerance and a system of indicators and alerts always unique for the organization. Compliance risks, including reputational risks, can increase strategic risks in the banking sector [4]. Studies showed that simplifying banking business models is necessary [5], and more consistent and cheaper compliance procedures could be made possible [3]. Compliance management is more than a bureaucratic fulfilment of requirements. It has a business dimension [6] with increasing importance and complexity. Its main challenges include a lack of dedicated local compliance experts, incomplete indicators, hidden risks in third-party relationships, and rapidly changing regulatory requirements (for example, COVID-19 pandemic social distancing, loan moratorium, and commercial sanctions) [7].

The compliance scope and activities are becoming highly complex in an increasingly fast-changing and globalized world. Thus, the risk assessment processes must be developed to keep up with the increasing complexity. The most cited risk assessment methods follow the requirements of the increasing complexity of the assessment process [8]. The two most popular ways include combining risk assessment approaches with Multi-Criteria Decision-Making (MCDM) methods and fuzzy applications to describe complex phenomena more accurately. As typical risk assessment techniques in many industries, risk matrices and the Failure Mode and Effect Analysis (FMEA) have numerous development directions in recent decades. As a novel risk assessment technique built on the factors of FMEA, the PRISM method focuses on assessing partial risks that can stay hidden and lead to severe effects [9]. Similar to the PRISM method, Ouyang et al. [10] also described a possible way to detect hidden risks. That method can also be a sound basis for bank compliance risk assessment.

As many references show [2, 4, 11, 12], the assessment of bank compliance risk is a significantly complex process that has many different evaluation factors. On the other hand, the existing methodological tools are just following the continuously gaining complexity of bank compliance assessment. Although some quantitative and deterministic approaches have already been described [2, 9] and PRISM method is focusing on hidden risk identification, many possible approaches still need to be added to the toolset, which could strengthen the methods' reliability in providing information related to the compliance risk set of a bank. In bank compliance management, hidden risks can seriously damage the organization's reputation, and spillover effects can cause a further threat to the entire sector [13].

The purpose of the study is to develop a novel PRISM risk assessment technique that can deal with the following criteria: the method should not use a deterministic scale-based risk assessment (1); the method can be applied for testing the consistency of the assessors (2); the similarities and dissimilarities of the assessors' results can be compared to each other in detail; thus, the uncertainty of the group level decision can be reduced (3); and the new method must provide the same ability in hidden risk detection than the initial PRISM method (4). With this improved skillset, the novel PRISM method can be a more robust approach to complex risk assessment just like bank compliance risk assessment.

The paper is organized as follows. Section 2 presents the compliance management and risk assessment background of the study. Section 3 introduces the proposed methodology in detail. Section 4 presents a case study in the banking sector and highlights the results of applying the method. Section 5 discusses the results. Finally, Section 6 summarizes the most important added values of the proposed methodology and propositions for future research.

2. Literature Review

First, the bank risk and compliance risk studies are presented. Next, the ISO 37301:2021 Compliance management system standard is introduced. Then, the compliance risk assessment literature is summarized.

2.1. Bank and Compliance Risk. The Basel Committee on Banking Supervision introduced the risk-based approach in the banking sector; nowadays, it has become business as usual. According to [14], out of the four main bank risks (liquidity, interest rate, capital, and credit risk), credit risk is generally viewed as critical regarding its impact on bank performance and failure. However, according to [15], the relationship between the effectiveness of risk management and bank risk is more significant in countries with higher institutional quality and standards. Empirical studies show that countries with better institutional systems are less likely to experience a banking crisis [16] which goes hand in hand with economic crises.

Moral hazard is a significant problem in liberalized financial systems, where there are more risk-taking opportunities [17]. Regulatory and supervisory practices (e.g., accurate disclosure of information) contribute to the performance and stability of the bank [18]. Tran et al. [19] used accounting and market-based risk measures in their study, finding that bank risk is negatively related to credit information sharing, which reduces the adverse effects of credit shocks on bank stability.

A three-step procedure has been created by Bezrodna [4] for assessing the bank's strategic risk and supporting its relationship with the compliance risk of financial monitoring. One finding is that compliance risk triggers an increase in strategic risk due to the application of financial sanctions against the bank. These may lead to reputational risks, negatively affecting the strategy's effectiveness. Furthermore, a significant difference between the actual and planned values of the indicators, or the inadequacy of the bank's strategic management mechanism, may lead it to focus on a formal approach to compliance with financial monitoring legislation [4]. The work of Birindelli and Ferretti [20] describes the similarities between operational risk and compliance risk and identifies areas of collaboration to achieve cost synergies and improved operational efficiency.

Many research studies [21–24] suggest that the committees that meet regularly during the financial year are linked to effective monitoring. As a result, audit committee effectiveness can reduce risks and increase banks' stability for regulatory compliance [25]. However, another study by Nguyen [24] shows that the audit committee's independence, number of meetings, and financial expertise negatively affect the risk-taking behavior of traditional banks.

As for Islamic banks, Masood et al. [26] showed that they develop and practice more robust techniques to manage their credit risk in addition to traditional methods, compared to non-Islamic banks. Empirical evidence [27] shows that Islamic banks below the target risk level tend to exhibit risk-seeking behavior. Also, Islamic banks with a higher loan-to-total assets ratio tend to take lower risks. A model has been developed by Ashraf and Lahsasna [28] to quantify

the Shariah risk and the level of Shariah compliance taken by Islamic banks, which can supplement traditional counterparty risk rating models.

In addition, a higher frequency of Sharia committee meetings reduces the risk of Sharia noncompliance in Islamic banks [29]. The impact of political connections on Shariah compliance of Islamic banks was examined by Syaputri and Nainggolan [30], finding that politically connected banks can reduce the risk of Shariah noncompliance better than nonpolitically connected Islamic banks.

Compliance risk is any event with a negative legal or reputational consequence. Most businesses have a strategically defined appetite and tolerance for risk that depends on several factors. Moreover, risks have a spillover and multiplier effect and can reinforce each other. Salvioni et al. [11] proposed a responsibility-oriented approach to compliance risk management, claiming that the lack of ethics in business operations, masked by formal compliance, often results in indirect adverse effects on the relationships between stakeholders.

2.2. Compliance Management Systems. In 2021, the International Organization for Standardization (ISO) issued a new standard, the ISO 37301:2021 Compliance management systems—Requirements with guidance for use [31], that supersedes the ISO 19600:2014. The main change is shifting from guidelines to requirements and the possibility of certifying the CMS against the standards. The general elements of a CMS are shown in Figure 1.

The organization and its legal, social, and cultural context are fundamental to the compliance management system. Understanding the context means considering several issues, including the business model, size, and the complexity and sustainability of the organization's activities and operations [31].

Besides the effect of the context, the top part, namely, objectives and principles, has a significant effect on how a compliance management system is designed and developed. Out of the objectives, reputation should be highlighted. A good reputation is usually the result of years of excellent expertise and cannot be created overnight [32]. Therefore, management needs to be aware of the reputation and emphasize it as a business resource. Reputational capital is the part of market value attributed to a firm's view as a responsible corporation [33].

The principles of the CMS are integrity, good governance, proportionality, transparency, accountability, and sustainability. One goal of mature compliance management is ensuring the integrity of the entire organization and its employees through the organization's leadership and management system [34–36]. Integrating good governance with a risk-based compliance function can improve performance efficiency and effectiveness [37]. According to [38], creating an effective internal control environment can mitigate or eliminate risks to corporate sustainability. Though not expressed explicitly, Governance, Risk, and Compliance (GRC) is the dominant approach in the ISO 37301:2021.

Figure 1: A simplified presentation of the elements of a compliance management system (edited version of ISO 37301:2021).

The center of Figure 1 shows the PDCA cycle, a four-step improvement planning tool. Governance, in the middle, refers to the comprehensive system of rules, practices, and standards that govern an enterprise. Leadership and culture are connected to all steps of the development cycle.

Identifying potential threats to a business is part of the Plan phase. This phase includes determining the scope, creating compliance policies, and clarifying roles and responsibilities. Design of operations and identification of compliance risks are also included here. So what are compliance risks? According to ISO 37301, compliance risk is the likelihood of occurrence and the consequences of noncompliance with the organization's (mandatory or voluntary) compliance obligations [31]. A practical and developed CMS aims to minimize the risk and consequences of noncompliance with obligations. Creating commitment at all levels is another ongoing task in the massive step of planning.

Compliance in action creates and uses processes and controls to ensure that the company and its employees conduct their business legally and ethically. Taking action to reduce or eliminate the effects of compliance risks is part of the Do phase. This phase also includes raising awareness, providing communication channels, training to elevate competence, and documentation.

Internal compliance audits, management reviews, monitoring, and measurement activities constitute the Check phase. Raising concerns and investigations are also included here.

The last phase is about refining the activities of the previous phases and continual improvement. Managing noncompliance, either prevention or correction, is part of this phase. Finally, ISO 37301 requires organizations to maintain documented information on compliance risk assessment, records of nonconformities, and investigations.

2.3. Compliance Risk Assessment. Every company that implements a compliance risk management program develops a self-developed process-based solution adapted to the needs and characteristics of the organization, reflecting regulatory and internal needs [2]. A compliance risk assessment program can be a helpful management tool because companies can reduce the number and severity of compliance incidents and improve their business operations by better identifying compliance risks and managing behaviors [39].

Standardized risk prevention requires identifying and quantifying risk based on risk assessment methodologies. Risk identification usually describes the following characteristics of a risk, its nature, source, and impact, for example, incident, business line, and regulatory outcome [40]. The risk matrix is a widely used risk assessment method in the banking sector that uses two rating factors, usually to estimate the "occurrence" and "severity" dimensions of risk incidents [2]. Kim et al. [41] analysed risk assessment standards and proposed a new method for identifying and evaluating financial information security risks through correlation analysis between various security standards and requirements. Naheem's [12] study concluded that risk assessment strategies remain largely reactive, leaving banks exposed to not realizing the risk by failing to conduct an assessment. The practical implications call for a more holistic, future-oriented approach from the bank's perspective [12].

The so-called "compliance dilemma" is a collective term for conflicts over the exercise of compliance activities within a company. For example, a compliance dilemma is when a manager perceives a contradiction between a legitimate decision-making alternative and an alternative that fits the organization's (e.g., financial) goals [42]. A study examining the minutes of the board meetings of Indian banks found that bank boards generally underinvest in risk and overinvest in regulation and compliance [43].

Organizations that aim for competitive advantage, organizational sustainability, and business success shall create a culture of compliance, a set of values, beliefs, and behaviors that create the norms that promote compliance. Compliance culture enhances such norms, attitudes, and work styles (i.e., accountability) that make compliant behavior possible and preferred and is the general basis for decision-making. The incentive structure and the consistency of formal risk management with actual behavior may support creating and developing a compliance culture [44].

Risk control and mitigation aim at reducing the likelihood of failure causes and their negative impact. The implementation of risk mitigation measures is prioritized and scheduled due to the availability of professional and financial resources. Banks use various control mechanisms (like internal procedures, the "four eyes" principle, Chinese walls, and access rights) to decrease risks [2].

In practice, compliance risk management is heavily based on consultations with expert groups, while the reliability of these consultations is rarely validated. Failure Mode and Effect Analysis is a widely used risk management methodology in most industries, including the banking sector. Instead of a standard risk matrix [2], FMEA applies three rating factors (severity, occurrence, and detectability) for risk assessment. The FMEA aims to assess failure modes related to a process or product and then reduce the risks via risk mitigation action plans [45]. The Partial Risk Map (PRISM) methodology is a novel risk assessment technique that closely resembles the risk assessment process of the FMEA. The basics of the PRISM method are described [9], and potential development areas are also addressed related to the methodology and application fields [46, 47]. Since compliance risk assessment is a complex evaluation and ranking process, MCDM methods are relevant methodological solutions for modeling complexity in the decision-making process. The possible classification of MCDM universe is presented by Cinelli et al. [48], and there are other significant works comparing different MCDM methods. In the work of Valipour et al. [49], seven different MCDM methods are applied for PPP project assessment, including pairwise comparison techniques and outranking methods in some cases combined with fuzzy logic. Analytic Hierarchy Process (AHP) is combined with Multi-Choice Goal Programming (MCGP) to project selection and resource allocation in risk-based internal audit planning [50]. For Risk Priority Number (RPN) calculation, Djenadic et al. [51] combined AHP with TOPSIS in a fuzzy environment in order to model uncertainty among expert choices.

Since pairwise comparison techniques are applied in the literature for factor weight calculation, the primary identified development direction of the PRISM method is based on pairwise comparison methods. Thus, the risk assessment process can be opened for subjective weightings. Another advantage of the combination with pairwise comparison methods is that the consistency of the experts can be tested [50–52], while this option is not applicable in the original PRISM method. This shortcoming of the PRISM method can be vital in bank compliance risk assessment; thus, combining the method with pairwise comparison techniques is highly suggested.

Applying pairwise comparison methods is a traditional basis for assessing and evaluating complex systems [38, 53]. Typical solutions of pairwise comparisons are the Guilford method [54], where only the preferences between the elements of pairs are determined, and the methodology of the AHP, where the strength of the preferences is also set [55]. Best Worst Method (BWM) is a preferred pairwise comparison technique if a large number of items should be compared while also setting the strength of preferences [56]. All methods give feedback on the consistency level of the experts [52, 56–58]. The Guilford method can be advised as a primary pairwise comparison technique of compliance risk assessment. Since the compliance risk assessment used to be a significantly subjective process due to the complex nature

of bank compliance, preference determination is also subjective. Setting preferences' strengths can cause an uncontrolled level of subjectivity in the assessment.

Total elimination of the risk of noncompliance is impossible; however, residual risks must be controlled and monitored. The risk-based approach to verifying compliance with a sound compliance culture can deliver significant cost savings while leading to better business management and greater flexibility in response to changes in the business context [59]. Naheem's [60] study supports the argument for integrating social corporate responsibility and anti-money laundering compliance, in contrast to the current practice of profit and business being seen as separate rather than integral to regulation and control. Authorities increasingly rely on risk assessment techniques to increase their regulatory effectiveness, for example, by increasing supervision of companies with high-risk profiles, assuming high levels of disclosure [61].

Compliance risk assessment has complex methodological options, and it is unique to each organization. Therefore, the consistency check of the experts is an advantage of a risk assessment technique, especially when the assessment is complex, just like in the case of bank compliance. The proposed pairwise comparison-based Partial Risk Map method is described in the following section.

3. Methods

The process flow of the proposed extended PRISM method is introduced in detail in Figure 2. The detailed formal description of the prosed method follows the visual process flow.

The first step is forming a set of comparable elements, while the focus group of the experts can also be established. The second step is creating the pairwise comparison sheets based on Ross's optimal order [62, 63] separately to the occurrence, severity, and detection rating factors.

Let n indicate the number of incidents. Thus, p number of pairs can be formed based on equation

$$p = \frac{n(n-1)}{2}. \tag{1}$$

The third step is setting the experts' priorities and checking the experts' consistency. The level of consistency can be calculated based on equation

$$K = 1 - \frac{d}{d_{\max}}. \tag{2}$$

In equations (2)–(4), $d_{\max}$ represents the highest possible number of inconsistent triads in a pattern. In the case of odd n:

$$d_{\max} = \frac{n^3 - n}{24}. \tag{3}$$

In the case of even n, the equation of $d_{\max}$ is the following:

$$d_{\max} = \frac{n^3 - 4n}{24}. \tag{4}$$

In equations (2) and (5), d represents the number of inconsistent triads in a certain paired comparison pattern, and it is calculated using the following formula:

$$d = \frac{n(n-1)(2n-1)}{12} - \frac{\Sigma a_i}{2}, \tag{5}$$

where a_i indicates how often a specific i element was preferred to the other elements.

Based on a chi-square distribution significance test, whether a certain d number of inconsistent triads indicates a random or systematic inconsistency in a pairwise comparison pattern can be identified. For calculating the degree of freedom (DF) for the chi-square distribution, equation (6) can be used:

$$\mathrm{DF} = \frac{n(n-1)(n-2)}{(n-4)^2}. \tag{6}$$

Equation (7) is applied to calculate the chi-square value:

$$\chi^2 = \frac{8}{(n-4)}\left\{\frac{1}{4}\left(\frac{3}{n}\right) - d + \frac{1}{2}\right\} + \mathrm{DF}. \tag{7}$$

In the case of systematic inconsistency, the individual assessment results cannot be used for further calculations.

As for the fourth step, a similarity check of the ranks of the incidents related to each consistent pattern should be executed. Based on testing the similarity, it can be decided whether the patterns can be aggregated—forming a group assessment result—or not. In the case of two ranks, rank correlation analysis can be applied to check the level of similarity. In the case of more than two ranks, aggregation can be executed or rejected based on the result of rank concordance analysis. This paper's similarity analysis is based on the calculation of Spearman's rho [64] in the case of two rankings and the calculation of Kendall's W [65] in the case of more than two rankings.

The value of Spearman's rank correlation coefficient is between −1 and 1. If the ranks are the same, Spearman's rho will be 1. If the ranks are opposite, Spearman's rho will be −1. If the ranks are independent, Spearman's rho will be 0. The value of Kendall's W coefficient is between 0 and 1. In the case of the same ranks, the value of W is 1. If the ranks are opposite, the coefficient will be equal to 0. A 5% significance level is offered to test rank similarity in the case of both coefficients.

If the ranks are similar, the results of the individual assessments can be aggregated in the fifth step of the process. After the aggregation, it can be calculated how often a specific i element was preferred to the other elements in the aggregated pattern. Let c_i indicate the number of preferences in the aggregate matrix. Then, the p_c values can be calculated based on equation (8), where k is the number of consistent experts.

$$p_c = \frac{c_i + (k/2)}{nk}. \tag{8}$$

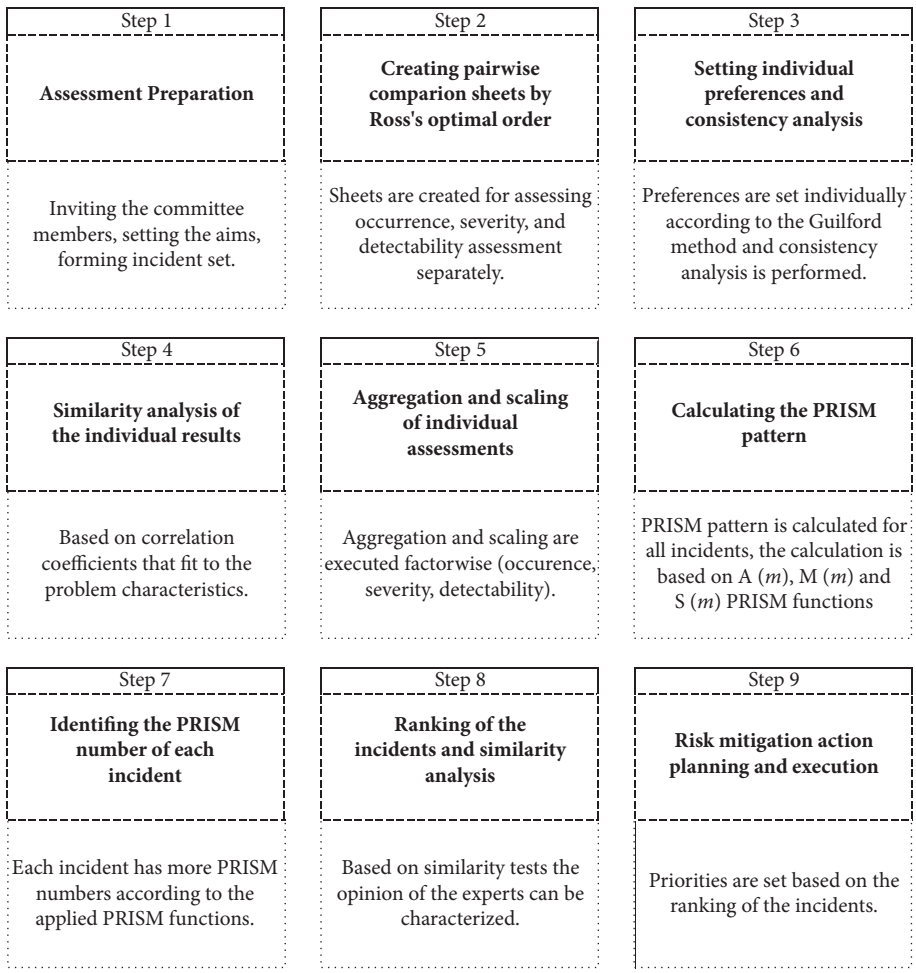

Figure 2: The steps of the proposed method.

Since the Guilford method ranks the comparable elements, it is necessary to introduce two theoretical variables representing the possible highest (C_1) and lowest (C_2) values of c_i. Based on equations (9) and (10), the value of C_1 and C_2 can be calculated.

$$c_{C1} = (n-1)k, \tag{9}$$

$$c_{C2} = (n-1)0 = 0. \tag{10}$$

The results of the Guilford method are projected to an interval scale by applying C_1 and C_2 values. Let u indicate the inverse normalized value of p_c. Linear transformation can transform u values to a selected scale [54, 58].

Since the values of occurrence, severity, and detection factors can be calculated related to each incident, as for the sixth step, the PRISM patterns of the incidents can also be set (see Figure 3). Since the PRISM methodology calculates the aggregate values of the paired rating factor values of an incident, denote $p(m) = p(o, s, d) := (o \otimes s, o \otimes d, d \otimes s)$ as the PRISM pattern of incident m.

In the seventh step, the PRISM number of a particular incident can be calculated by selecting the maximal value of the three aggregates of p (m). To test the validity of the

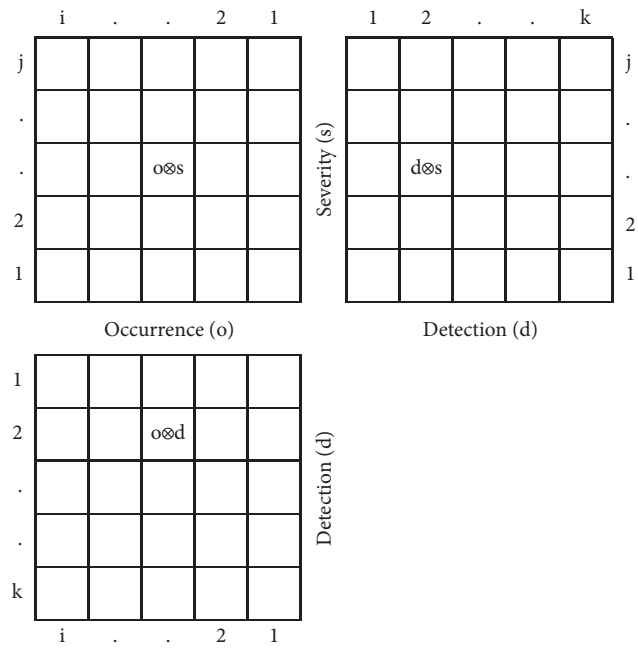

Figure 3: The PRISM pattern of an incident.

results, multi-assessment is performed, applying different threshold lines (linear, convex, and concave) in the submatrices of the PRISM. Equations (11)–(13) are applied in this study based on [66].

$$A(m) = \max(o + s, o + d, d + s), \tag{11}$$

$$M(m) = \max(o \cdot s, o \cdot d, d \cdot s), \tag{12}$$

$$S(m) = \max\left(o^2 + s^2, o^2 + d^2, d^2 + s^2\right), \tag{13}$$

where $A(m)$ function results in linear, $M(m)$ results in convex, and $S(m)$ results in concave threshold lines from the perspective of the center of the PRISM [66].

In the eighth step, the individual and aggregated prioritization of the incidents can be executed based on the PRISM numbers. Applying $A(m)$, $M(m)$, and $S(m)$ functions, the similarity of the same expert rankings can be tested, providing feedback on the validity of the assessment. In addition, outlier experts can be identified by testing the similarity of the aggregated ranking and the individual rankings. Both tests strengthen the proposed method's reliability, which is necessary for the subjective assessment of complex phenomena.

Based on the result of the prioritization, further risk reduction actions can be planned and launched in the ninth step.

4. Case Study

In 2021, a risk assessment workshop was launched in the compliance management directorate of one of the largest Central and Eastern European banks. After collecting bank branch-related compliance incidents, a focus group of the three top compliance experts was established. The focus group members had more than ten years of experience in the compliance management field in the commercial bank sector. This study presents the pairwise comparisons of six randomly selected incidents.

The experts assessed the cases (see Table 1) based on Guilford's pairwise comparison method. The assessment was executed three times since the cases had to be assessed based on the occurrence, severity, and detection factor. The results are given in Appendix A. Based on the Chi-Square statistic, if there are more than two inconsistent triads in a pattern ($d > 2$), the decision maker is inconsistent at a 0.05 significance level. Hence, the result of the consistency evaluation of the experts showed that Expert 1 and Expert 2 were consistent in the occurrence, severity, and detection-based comparisons. In contrast, Expert 3 was consistent only in the severity-based comparison. The results of the consistency tests are given in Table 2.

The similarity test of the ranks can be executed after the consistency test. In the case of the severity factor, all the experts were consistent (Kendall's W is calculated). In contrast, two experts can be involved in the case of the occurrence and the detection factors (Spearman's rho is calculated). Kendall's W is 0.947 at a 0.014 significance level in the case of the severity factor (all experts were consistent). In the case of the occurrence factor, Spearman's rho is 0.829 at 0.042 significance level (only Expert 1 and Expert 2 were consistent). In the case of the detection factor, Spearman's rho is 0.883 at a 0.02 significance level (Expert 1 and Expert 2 were consistent).

Since the patterns are significantly similar, the aggregation by factors can be executed. The results of the aggregation are given in Appendix B.

Based on the scale values of the occurrence, severity, and detection factors, the PRISM patterns of the incidents can be visualized (see Figure 4). The PRISM numbers are also visible in Figure 4 based on the maximal values of each case (see Table 3). The PRISM numbers are indicated with a dashed outline and darker color (see Figure 4) and bold numbers (see Table 3).

In this case study, A (m), $M(m)$, and $S(m)$ functions give the same rankings related to the aggregated results, although the rankings could differ by function. In the case of Expert 1, different functions result in different rankings, while in the case of Expert 2, the rankings by different functions are the same. Expert 3 has no consistent occurrence and detection-related pairwise comparison results. Thus, for Expert 3, the PRISM cannot be constructed because of two missing factors.

Testing the impact of each expert's rankings on the aggregated ranking is optional, but it can highlight significant results of the entire analysis. The test can also help identify the best-fitting and outlier experts. Based on the data in Appendix A, the PRISM rankings of Expert 1 and Expert 2 can be calculated. After that, rank correlation analysis can be performed to describe the correlations between each expert's ranking and the aggregated ranking. The higher the correlation coefficient value, the better the fit to the aggregated rankings. If the significance level of the correlation coefficient is lower than 0.05, the expert will be marked as an outlier expert. Spearman's rho is applied for the calculation.

The rankings of each expert related to the $A(m)$, $M(m)$, and $S(m)$ functions are visible (see Table 4), as well as the aggregated rankings. Since the aggregated rankings and Expert 2's rankings have no differences by the PRISM functions, these rankings are placed in the table only once.

Since $A(m)$, $M(m)$, and $S(m)$ functions resulted in different rankings in the case of Expert 1, it is necessary to test the similarity of the rankings of Expert 1. For testing the similarity, Spearman's rho is calculated (see Table 5).

The correlation coefficients are high in all the comparisons, and the significance level was higher than 0.05. Thus, there is no outlier expert in the analysis, and the rankings of Expert 1 are similar. Without applying further nonparametric tests (Kendall's W), it can be identified that $S(m)$ function gives the most similar expert rankings.

Based on the results, C6 has the highest relative partial risk in the analysis. Thus, it is the riskiest incident. Since this top partial risk can be identified in the occurrence vs. detection submatrix, the possible optimal development or risk mitigation strategy is to decrease the occurrence level or increase the detectability level of the incident.

As all the consistent experts agreed, C5 is the least risky incident. There are slight changes in the ranks of C1, C2, C3,

Table 1: Randomly selected risks involved in the risk assessment.

Case	Function/process step	Potential failure	Potential effects of failure
C1	Cash withdrawal in a bank branch	A young person accompanies the elderly customer	Client losing wealth
C2	Looking into client accounts	Checking acquaintance's account after a phone call on business mobile	Protocol violation
C3	Replying to a customer inquiry about account abuse	Customer misinformation, and lack of reporting to bank security	Client losing wealth, security incident
C4	Cash withdrawal, account closing	The legal representative of a minor client withdraws the total amount and closes the account	Minor client losing wealth
C5	New account opening	A bank clerk opening a new account for a family member	Conflict of interest, protocol violation
C6	Offering travel insurance	Lack of reporting foreign card use	Credit card abuse

Table 2: Results of the consistency test.

Factor	Index	Expert 1	Expert 2	Expert 3
O	d	0	0	4
	K	100%	100%	50%
S	d	0	0	1
	K	100%	100%	87.5%
D	d	0	2	3
	K	100%	75%	62.5%

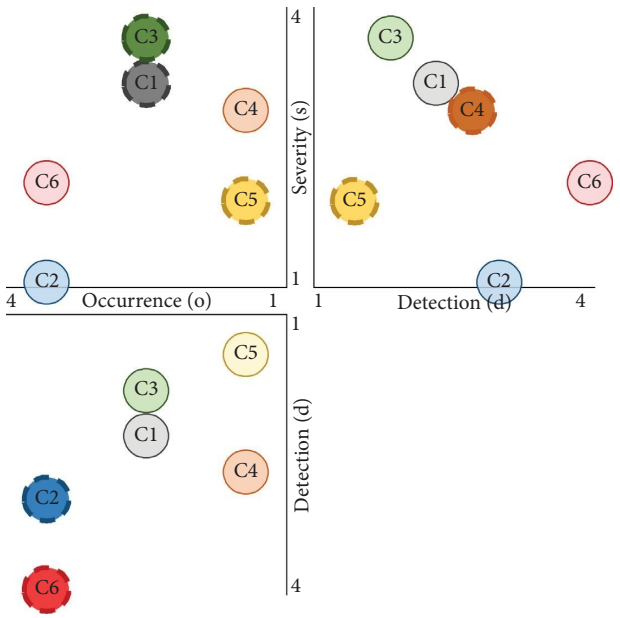

Figure 4: The visualization of the PRISM patterns and the PRISM numbers of the incidents.

Table 3: PRISM numbers based on the aggregated values in Appendix B.

	Case	*o-s*	*o-d*	*d-s*	Max	Rank
A (m)	C1	**8.1**	5.7	7.3	8.1	4
	C2	3.5	**10.5**	3.0	10.5	2
	C3	**9.2**	4.4	6.5	9.2	3
	C4	4.2	4.0	**7.9**	7.9	5
	C5	**2.8**	2.1	**2.8**	2.8	6
	C6	7.5	**14.2**	8.5	14.2	1
M (m)	C1	**5.7**	4.8	5.5	5.7	4
	C2	4.5	**6.5**	4.0	6.5	2
	C3	**6.2**	4.3	5.4	6.2	3
	C4	4.3	4.2	**5.6**	5.6	5
	C5	**3.4**	2.9	**3.4**	3.4	6
	C6	5.7	**7.6**	6.1	7.6	1
S (m)	C1	**16.7**	11.4	15.6	16.7	4
	C2	13.6	**21.4**	9.8	21.4	2
	C3	**19.8**	9.4	16.7	19.8	3
	C4	10.4	9.5	**15.8**	15.8	5
	C5	**5.9**	4.2	**5.9**	5.9	6
	C6	17,1	**28.6**	20.5	28.6	1

The bold values are highlighting the PRISM numbers.

Table 4: Rankings by experts and functions.

Cases	Expert 1			Expert 2	Aggregated ranking
	A (m)	M (m)	S (m)		
C1	4	5	4	4	4
C2	3	3	3	2	2
C3	2	2	2	3	3
C4	4	4	5	5	5
C5	5	6	6	6	6
C6	1	1	1	1	1

Table 5: Correlation coefficients of the similarity tests.

	Expert 1		Expert 2	Aggregated ranking
	M (m)	S (m)		
Expert 1 (A (m))	0.986	0.986	0.928	0.928
Expert 1 (M (m))		0.943	0.886	0.886
Expert 1 (S (m))			0.943	0.943
Expert 2				1.000

and C4 applying different functions, but as the analyses showed, these changes are moderate.

Since only significantly consistent experts were involved in the aggregated assessment and the individual assessments were similar, it can be concluded that the assessment is based on adequate knowledge, and the results are reliable.

5. Discussion and Managerial Implications

5.1. Discussion. A risk-based approach in compliance management is best practice internationally [37, 59], and reducing risks requires company-wide collaboration. However, breaking down principles and theories into methods and techniques is challenging and highly dependent on industry, size, and strategy. Therefore, compliance risk management is always unique for the organization. Understanding the legal and business context is critical in planning and operating a compliance management system [31, 36].

Effective compliance programs identify and control risks that could lead to financial and reputational loss or legal consequences [67]. Many indicators used to monitor compliance risks are also used to monitor operational risks. Therefore, an integrated operational and noncompliance risk framework can lead to practical solutions and reduced costs [68]. Appropriate techniques for the risk-based approach are listed in Annex B of IEC 31010:2019, which contains 31 risk assessment techniques, including Failure Mode and Effect Analysis (FMEA) [69]. In reality, methods and techniques are often determined by the practices and preferences of stakeholders and parent companies [70]. Risk assessment is helpful in the design phase of new products, services, or processes and for actual business processes. In practice, compliance risk management is heavily based on

consultations with expert groups, while the reliability of these consultations is rarely validated.

The risk matrix is a widely used risk assessment method in the banking sector, which has several weak points. First, the risk matrix is created along only two dimensions. The "probability" dimension is essentially the same as the "occurrence" factor of the FMEA. In contrast, "impact" is essentially the "severity" of the consequences of a failure mode in the FMEA. The issue of detectability is typically left out of the traditional risk matrix. In some cases, users interpret it as part of the probability, i.e., it is confused with the simple frequency of occurrence in the probability dimension. In addition to the advantages of the detectability dimension, with the help of the proposed pairwise comparison-based PRISM method, experts can check the consistency of individual decisions and identify outliers.

This study focuses on the assessment of partial or hidden risks. According to [71], knowledge discovery based on MCDM methods is a widely emerging field of the risk management of financial institutions. Combining the PRISM method with Guilford's pairwise comparison is an alternative to the original PRISM method, which uses deterministic scales for assessing the FMEA factors. When assessors compare the alternatives in pairs to judge which is preferred in light of a rating factor (like severity), the method allows testing the decisions' inconsistency. The consistency testing of expert evaluations is an advantage in highly complex matters. On the one hand, the main result of the risk assessment is the aggregated ranking of risks. On the other hand, outlier experts can be identified based on testing the impact of individual expert rankings on the aggregated ranking.

Based on the prioritization of the incidents by PRISM numbers, possible risk mitigation or reduction actions can be planned and launched. However, organizations should reassess risks periodically. In addition, reassessment is needed when new activities are launched and significant external changes (like a pandemic or war situation) or changes in the organizational structure (like mergers and acquisitions) happen.

On the one hand, risk management aims to control and reduce the likelihood of errors in compliance and the scope of their negative consequences [2]. On the other hand, actions may aim at improving the detectability of issues by designing controls within the processes. A common pitfall of compliance risk assessment is when management has already decided, without understanding the underlying causes, which risk they want to address in the next period. In the case of forced solutions, risk mitigation is artificially prioritized.

5.2. Managerial Implications in Light of the Proposed Methodological Process and the Shortcomings of the Bank's Practice. The compliance risk assessment process is qualitative and based on historical data if data are available. The group assessment is based on discussion; no individual assessments are performed. The bank uses the risk matrix technique for risk assessment practices related to noncompliance events. Since many banks have the same main compliance management processes, practical observations can be made based on comparing the bank's compliance risk assessment process and the proposed process. The risk matrix determines the degree of risk based on predefined scales to assess the probability of occurrence and severity of impact. Figure 5 shows the structure of the matrix.

Determining the likelihood of the issue occurring describes the possibility in the foreseeable future. The probability of noncompliance events or their causes can fall into four categories: unlikely (happens once in more than five years), possible (happens every 3–5 years), likely (happens every 1–3 years), and very likely (occurs within 12 months). Often, historical data analysis is included in the estimation of incident occurrence.

The severity of noncompliance events is classified as follows: low (no or little financial loss, no reputational impact), medium (small financial loss, slight negative regional-level reputational impact), significant (significant financial loss or regional reputational impact, legal consequences), and severe (severe financial or legal consequences or global reputational impact).

The overall compliance risk rating can be aggregated into four categories: minor, moderate, significant, and critical. The risk rating is represented in four colors (green, yellow, orange, and red), where the yellow and orange categories are warnings and encourage corrective measures. Some corrective action is required for risks at any level over the minor. Based on the risk matrix, experts can visualize the accumulated risk of certain operations or departments.

The first problem of the risk matrix technique is that the risk matrix does not involve the ease of detection of failures and causes of noncompliance. Obviously, if a failure is harder to detect, it will pose more risk on the operations. PRISM and any FMEA-based methods dealing with severity, occurrence, and detection rating factors provide a basic solution for this practice.

The second major problem with the practice of bank is that applying predefined scales for the assessment does not allow for testing the consistency of the experts. The combination of the PRISM method with pairwise comparison techniques solves this problem. Since in the practice of the bank only group assessment is performed, the control possibilities of any individual expert results are unfeasible. Thus, important information related to similarity measure testing cannot be provided, for example, outlier experts cannot be identified. The proposed risk assessment process is based on the aggregation of individual results, so the previously mentioned problem of the bank's process can be solved. In the bank practice, there are only four outputs as for the result of the risk assessment (minor, moderate, significant, and critical), so in case of many assessable issues, many items will have the same output value. Thus, in the case of scarce resources, there is no support information on which issue having the same output value should be mitigated first. Applying the proposed PRISM method, the final ranking will be more detailed than that in the bank practice. Although only a few problems were mentioned, hopefully, these can create motivation for the compliance experts of the

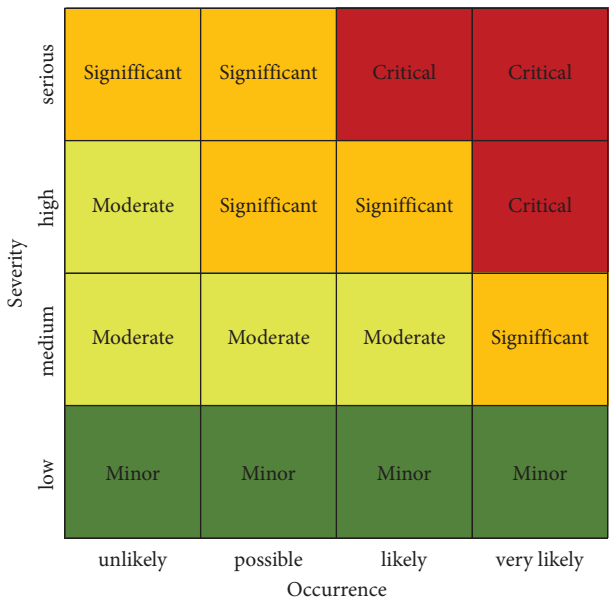

Figure 5: Risk matrix in the practice of the compliance office.

bank (and in other banks where the characteristics of the risk assessment processes are quite similar) to conceive developments in the compliance management system.

6. Conclusions

This article presented a new compliance risk assessment method based on a commercial banking case study. Compliance management refers to the processes and controls that ensure that a company and its employees conduct their business legally and ethically. ISO 37301:2021 is the contextual background where the risk approach to compliance management is the foundation. In practice, the most popular risk assessment methods are combined with Multi-Criteria Decision-Making methods to describe complex phenomena more accurately. The PRISM method based on pairwise comparisons aligns with this trend.

The new method highlights that pairwise comparisons can provide an opportunity to compare the risk rankings of compliance experts and their consistency with aggregate rankings. In addition, this method allows organizations to identify inconsistent and outlier experts. Significantly different assessments may include valuable insights into a particular phenomenon or differing interpretations of complex issues.

As a limitation, this case study was presented with only a small incident sample, but the results of statistical methodologies are valid. The agreement between the three organizational experts is significant. Furthermore, the case study did not examine whether the professional experience or the time spent at the particular bank was related to the rankings resulting from the evaluation.

A methodological limitation of this work is that the uncertainty related to the experts' opinions on the pairwise comparison process cannot be modeled well, since the proposed method applies binary output indicating the preferences. Instead of AHP and BMW methods which can be fuzzified well, in the case of the proposed method, fuzzyfication seems to be cumbersome. The Guilford method has almost the same limitation as the AHP, that is, the number of comparable items is quite low, according to human brain capacity. In the case of many comparable elements, the PRISM method should be integrated with BMW instead of binary techniques or AHP.

Future research could focus on decision-making and how group assessment techniques, such as the traditional FMEA, can be combined with individual assessment techniques. Another possible research direction is a methodological extension, namely, the combination of AHP or BWM and PRISM when the relationship between two risks (incidents) and the strength of the preferences are also included in the evaluations. Furthermore, since fuzzyfication is a developing research field besides the MCDM methods [72] in the description of complex systems, the fuzzy-based hybrid development of the PRISM method can also be a possible future development direction. Fuzzy logic is efficient for handling uncertain and imprecise knowledge, which is sometimes the case in the bank compliance area. Similarly, since risk factor estimations are based on previous observations and experience, the consideration of the uncertainty associated with these observations [73] and the risk of decision errors [74] is another route to extend the proposed method. Finally, future research could investigate the human element in compliance risk management, from individual characteristics that affect compliance dilemmas at work to compliance culture.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

Appendix A: the individual results of the pairwise comparisons. Appendix B: the aggregated results including the sufficiently consistent individual results. (*Supplementary Materials*)

References

[1] COSO, *Compliance Risk Management: Applying the COSO ERM Framework*COSO, Washington, WA, USA, 2020.

[2] E. Losiewicz-Dniestrzanska, "Monitoring of compliance risk in the bank," *Procedia Economics and Finance*, vol. 26, pp. 800–805, 2015.

[3] E. Losiewicz-Dniestrzanska and A. Nosowski, "The risk of non-compliance in the context of a banking business model," *New Trends and Issues Proceedings on Humanities and Social Sciences*, vol. 3, no. 4, pp. 198–207, 2017.

[4] O. S. Bezrodna, "Strategic risk of a bank: assessment proposals and interrelation with the compliance risk," *Business Inform*, vol. 12, no. 503, pp. 317–324, 2019.

[5] B. Makowicz, *Compliance W Przedsiębiorstwie"*, Oficyna Wolters Kluwer Business, Warszawa, Poland, 2011.

[6] P. Benedek, "Compliance management – a new response to legal and business challenges," *Acta Polytechnica Hungarica*, vol. 9, no. 3, pp. 135–148, 2012.

[7] M. Hashmi, G. Governatori, H. P. Lam, and M. T. Wynn, "Are we done with business process compliance: state of the art and challenges ahead," *Knowledge and Information Systems*, vol. 57, no. 1, pp. 79–133, 2018.

[8] H. C. Liu, X. Q. Chen, C. Y. Duan, and Y. M. Wang, "Failure mode and effect analysis using multi-criteria decision making methods: a systematic literature review," *Computers & Industrial Engineering*, vol. 135, pp. 881–897, 2019.

[9] F. Bognár and P. Benedek, "A novel risk assessment methodology: a case study of the PRISM methodology in a compliance management sensitive sector," *Acta Polytechnica Hungarica*, vol. 18, no. 7, pp. 89–108, 2021.

[10] L. Ouyang, Y. Che, L. Yan, and C. Park, "Multiple perspectives on analyzing risk factors in FMEA," *Computers in Industry*, vol. 141, Article ID 103712, 2022.

[11] D. M. Salvioni, F. Gennari, and L. Bosetti, "Global Responsibility and Risks of Compliance Failure in Emerging Markets," in *Risk Management in Emerging Markets*, S. Boubaker, B. Buchanan, and D. K. Nguyen, Eds., Emerald Group Publishing Limited, Bingley, UK, 2016.

[12] M. A. Naheem, "Anti-money laundering/trade-based money laundering risk assessment strategies – action or re-action focused?" *Journal of Money Laundering Control*, vol. 22, no. 4, pp. 721–733, 2019.

[13] C. Eckert and N. Gatzert, "The impact of spillover effects from operational risk events: a model from a portfolio perspective," *The Journal of Risk Finance*, vol. 20, no. 2, pp. 176–200, 2019.

[14] R. Boffey and G. N. Robson, "Bank credit risk management," *Managerial Finance*, vol. 21, no. 1, pp. 66–78, 1995.

[15] Q. K. Nguyen and V. C. Dang, "Does the country's institutional quality enhance the role of risk governance in preventing bank risk?" *Applied Economics Letters*, vol. 30, no. 6, pp. 850–853, 2022.

[16] A. Demirgüç-Kunt, E. Detragiache, and T. Tressel, "Banking on the principles: compliance with Basel core principles and bank soundness," *Journal of Financial Intermediation*, vol. 17, no. 4, pp. 511–542, 2008.

[17] A. Demirgüç-Kunt and E. Detragiache, "Cross-Country Empirical Studies of Systemic Bank Distress: A Survey," *National Institute Economic Review*, vol. 192, pp. 68–83, 2005.

[18] J. R. Barth, G. Caprio, and R. Levine, "Bank regulation and supervision: what works best?" *Journal of Financial Intermediation*, vol. 13, no. 2, pp. 205–248, 2004.

[19] S. Tran, D. Nguyen, K. Nguyen, and L. Nguyen, "Credit booms and bank risk in Southeast Asian countries: does credit information sharing matter?" *Asia-Pacific Journal of Business Administration*, 2022.

[20] G. Birindelli and P. Ferretti, "Compliance function in Italian banks: organizational issues," *Journal of Financial Regulation and Compliance*, vol. 21, no. 3, pp. 217–240, 2013.

[21] J. A. Conger, D. Finegold, and E. E. Lawler, "Appraising boardroom performance," *Harvard Business Review*, vol. 76, no. 1, pp. 136–148, 1998.

[22] L. J. Abbott, S. Parker, and G. F. Peters, "Audit committee characteristics and restatements," *Auditing: A Journal of Practice & Theory*, vol. 23, no. 1, pp. 69–87, 2004.

[23] B. Xie, W. N. Davidson, and P. J. DaDalt, "Earnings management and corporate governance: the role of the board and the audit committee," *Journal of Corporate Finance*, vol. 9, no. 3, pp. 295–316, 2003.

[24] Q. K. Nguyen, "Oversight of bank risk-taking by audit committees and Sharia committees: conventional vs Islamic banks," *Heliyon*, vol. 7, no. 8, Article ID e07798, 2021.

[25] Q. K. Nguyen, "Audit committee structure, institutional quality, and bank stability: evidence from ASEAN countries," *Finance Research Letters*, vol. 46, Article ID 102369, 2022.

[26] O. Masood, H. Al Suwaidi, and P. Darshini Pun Thapa, "Credit risk management: a case differentiating Islamic and non-Islamic banks in UAE," *Qualitative Research in Financial Markets*, vol. 4, no. 2/3, pp. 197–205, 2012.

[27] N. Alam and K. Boon Tang, "Risk-taking behaviour of Islamic banks: application of prospect theory," *Qualitative Research in Financial Markets*, vol. 4, no. 2/3, pp. 156–164, 2012.

[28] M. A. Ashraf and A. Lahsasna, "Proposal for a new Sharī'ah risk rating approach for Islamic banks," *ISRA International Journal of Islamic Finance*, vol. 9, no. 1, pp. 87–94, 2017.

[29] R. Basiruddin and H. Ahmed, "Corporate governance and Shariah noncompliant risk in islamic banks: evidence from southeast asia," *Corporate Governance: The International Journal of Business in Society*, vol. 20, no. 2, pp. 240–262, 2019.

[30] A. R. Syaputri and Y. A. Nainggolan, "Does political connection affect sharia non-compliance risk? Evidence from Indonesian and Malaysian Islamic banks," *Journal of Sustainable Finance & Investment*, pp. 1–27, 2022.

[31] ISO, *Compliance Management Systems - Requirements with Guidance for Use*, ISO, London, UK, 2021.

[32] J. A. Petrick and J. F. Quinn, "The integrity capacity construct and moral progress in business," *Journal of Business Ethics*, vol. 23, no. 1, pp. 3–18, 2000.

[33] C. J. Fombrun and M. Shanley, "What's in a name? Reputation building and corporate strategy," *Academy of Management Journal*, vol. 33, no. 2, pp. 233–258, 1990.

[34] D. Koehn, "Integrity as a business asset," *Journal of Business Ethics*, vol. 58, no. 1-3, pp. 125–136, 2005.

[35] L. Tourigny, W. L. Dougan, J. Washbush, and C. Clements, "Explaining executive integrity: governance, charisma, personality and agency," *Management Decision*, vol. 41, no. 10, pp. 1035–1049, 2003.

[36] R. Hendra, "Comparative review of the latest concept in compliance management & the compliance management maturity models," *RSF Conference Series: Business, Management and Social Sciences*, vol. 1, no. 5, pp. 116–124, 2021.

[37] F. Bezzina, S. Grima, and J. Mamo, "Risk management practices adopted by financial firms in Malta," *Managerial Finance*, vol. 40, no. 6, pp. 587–612, 2014.

[38] A. Boros and C. Fogarassy, "Relationship between corporate sustainability and compliance with state-owned enterprises in central-europe: a case study from Hungary," *Sustainability*, vol. 11, no. 20, p. 5653, 2019.

[39] S. Nicolas and P. V. May, "Building an effective compliance risk assessment programme for a financial institution,"

Journal of Securities Operations & Custody, vol. 9, no. 10, pp. 215–224, 2017.

[40] AIRMIC, *A Structured Approach to Enterprise Risk Management (ERM) and the Requirements of ISO 31000*, AIRMIC, London, UK, 2010.

[41] A. C. Kim, S. M. Lee, and D. H. Lee, "Compliance risk assessment measures of financial information security using system dynamics," *International Journal of Security and its Applications*, vol. 6, no. 4, pp. 191–200, 2012.

[42] G. Gösswein, "Mediation als Weg aus dem Compliance-Dilemma," *Die Mediation*, vol. 2, p. 42, 2017.

[43] S. Agarwal, S. Kamath, K. Subramanian, and P. Tantri, "Board conduct in banks," *Journal of Banking & Finance*, vol. 138, Article ID 106441, 2022.

[44] T. Poppensieker, S. Schneider, and M. Thun, "Financial institutions and non-financial risk: learning from the corporate approach," in *Non-Financial Risk Management: Emerging Stronger after Covid-19*, T. Kaiser, Ed., Risk Books, London, UK, 1st edition, 2021.

[45] J. Huang, J. X. You, H. C. Liu, and M. S. Song, "Failure mode and effect analysis improvement: a systematic literature review and future research agenda," *Reliability Engineering & System Safety*, vol. 199, Article ID 106885, 2020.

[46] A. Forgács, J. Lukács, and R. Horváth, "The investigation of the applicability of fuzzy rule-based systems to predict economic decision-making," *Acta Polytechnica Hungarica*, vol. 18, no. 11, pp. 97–115, 2021.

[47] P. Rosenberger and J. Tick, "Multivariate optimization of PMBOK, version 6 project process relevance," *Acta Polytechnica Hungarica*, vol. 18, no. 11, pp. 9–28, 2021.

[48] M. Cinelli, M. Kadziński, G. Miebs, M. Gonzalez, and R. Słowiński, "Recommending multiple criteria decision analysis methods with a new taxonomy-based decision support system," *European Journal of Operational Research*, vol. 302, no. 2, pp. 633–651, 2022.

[49] A. Valipour, H. Sarvari, and J. Tamošaitiene, "Risk assessment in PPP projects by applying different MCDM methods and comparative results analysis," *Administrative Sciences*, vol. 8, no. 4, p. 80, 2018.

[50] X. Wang, T. Zhao, and C. T. Chang, "An integrated FAHP-MCGP approach to project selection and resource allocation in risk-based internal audit planning: a case study," *Computers & Industrial Engineering*, vol. 152, Article ID 107012, 2021.

[51] S. Djenadic, M. Tanasijevic, P. Jovancic, D. Ignjatovic, D. Petrovic, and U. Bugaric, "Risk evaluation: brief review and innovation model based on fuzzy logic and MCDM," *Mathematics*, vol. 10, no. 5, p. 811, 2022.

[52] L. Berényi and N. Deutsch, "Corporate social responsibility and business philosophies among Hungarian business students," *Sustainability*, vol. 13, no. 17, p. 9914, 2021.

[53] J. Kiss, Z. Kosztyán, A. Németh, and F. Bognár, "Matrix-based methods for planning and scheduling maintenance projects," in *Invest on Visualization Proceedings of the 13th International DSM Conference*, S. D. Eppinger, M. Maurer, K. Eben, and U. Lindemann, Eds., pp. 421–434, Carl Hanser Verlag, München, Germany, 2011.

[54] J. P. Guilford, "The method of paired comparisons as a psychometric method," *Psychological Review*, vol. 35, no. 6, pp. 494–506, 1928.

[55] R. W. Saaty, "The analytic hierarchy process—what it is and how it is used," *Mathematical Modelling*, vol. 9, no. 3-5, pp. 161–176, 1987.

[56] J. Rezaei, "Best-worst multi-criteria decision-making method," *Omega*, vol. 53, pp. 49–57, 2015.

[57] M. Braglia, "MAFMA: multi-attribute failure mode analysis," *International Journal of Quality & Reliability Management*, vol. 17, no. 9, pp. 1017–1033, 2000.

[58] A. Buzási and B. S. Jäger, "District-scale assessment of urban sustainability," *Sustainable Cities and Society*, vol. 62, Article ID 102388, 2020.

[59] D. Batchelor, "Risk-based compliance monitoring," *Journal of Financial Regulation and Compliance*, vol. 7, no. 1, pp. 22–26, 1999.

[60] M. A. Naheem, "HSBC Swiss bank accounts-AML compliance and money laundering implications," *Journal of Financial Regulation and Compliance*, vol. 23, no. 3, pp. 285–297, 2015.

[61] D. De Widt and L. Oats, "Risk assessment in a cooperative compliance context: a Dutch-UK comparison," *British Tax Review*, no. 2, pp. 230–248, 2017.

[62] R. T. Ross, "Discussion: optimal orders in the method of paired comparisons," *Journal of Experimental Psychology*, vol. 25, no. 4, pp. 414–424, 1939.

[63] W. G. Cloete, I. Cloete, and K. von Gadow, "An algorithm for presenting pairs in optimum orders," *EDV in Medizin und Biologie*, vol. 19, no. 2-3, pp. 75–77, 1988.

[64] C. Spearman, "The proof and measurement of association between two things," *American Journal of Psychology*, vol. 15, no. 1, pp. 72–101, 1904.

[65] M. G. Kendall, *Rank Correlation Methods*, Griffin, London, UK, 1970.

[66] F. Bognár and C. Hegedűs, "Analysis and consequences on some aggregation functions of PRISM (partial risk Map) risk assessment method," *Mathematics*, vol. 10, no. 5, p. 676, 2022.

[67] SIA, "White paper on the role of compliance," 2005, https://www.sifma.org/wp-content/uploads/2017/08/2005RoleofComplianceWhitePaper.pdf.

[68] PWC, "Managing compliance and operational risk in the new environment," 2013, https://www.pwc.com/fsi.

[69] IEC, "Risk Management-Risk Assessment Techniques 31010: 2019," 2019, https://www.iso.org/standard/72140.html.

[70] P. Benedek, "Compliance management in services," *PhD Thesis*, , 2019.

[71] W. Wu, "Credit risk measurement, decision analysis, transformation and upgrading for financial big data," *Complexity*, vol. 2022, Article ID 8942773, 8 pages, 2022.

[72] M. Kelemen, V. Polishchuk, B. Gavurová et al., "Model of evaluation and selection of expert group members for smart cities, green transportation and mobility: from safe times to pandemic times," *Mathematics*, vol. 9, no. 11, p. 1287, 2021.

[73] C. Hegedűs and Z. T. Kosztyán, "The consideration of measurement uncertainty in forecast and maintenance related decisions," *Problems of Management in the 21st Century*, vol. 1, pp. 46–59, 2011.

[74] Z. T. Kosztyán, C. Hegedűs, and A. Katona, "Treating measurement uncertainty in industrial conformity control," *Central European Journal of Operations Research*, vol. 25, no. 4, pp. 907–928, 2017.

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Research Article

Connectedness of International Stock Market at Major Public Events: Empirical Study via Dynamic Time Warping-Based Network

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Several public events have drawn renewed attention to the connectedness of the international stock market since the financial crisis of 2008. We investigate systemic and regional connectedness among stock markets around the world at major public events by constructing correlation networks for 46 markets based on the dynamic time-warping method. We find that (i) geographic regionalization is typically observed in the stock market network, in which France is dominant, (ii) Europe has the greatest and the Middle East and Africa the least within-region connectedness, (iii) the correlation network structure is highly integrated and compact at major public events, and global events influence the international stock market more significantly than regional events do, and (iv) the importance of China reaches its peak during the era of Sino-US trade friction, showing that public events have enormous impacts on the countries involved.

1. Introduction

1.1. Background. Economic integration is a matter of great international concern. Connectedness among financial markets around the world is increasing. This deserves close attention due to the "too connected to fail" risk. Moreover, public events can exacerbate the spread of risk, resulting in financial crises and persistent impacts on national economies. Direct and indirect connectedness among financial markets is accelerating and making them increasingly closely related and interdependent, forming a complex financial network [1–3]. This connectedness is both diversifying financial risks and promoting their spread [4, 5]. Major public events have led to significant changes in the global financial system. Therefore, we focus on the correlation network of the international stock market at major public events.

Recently, the uncertainty of the COVID-19 epidemic has had a negative impact on the global economy. Panic-induced asset sales occurred in the highly leveraged financial market in March 2020. The price of crude oil fell sharply, and the ratings of US shale oil companies were downgraded. In the international stock market, three major US stock indices triggered the first-level circuit breaker mechanism. Over 10 days, the market experienced four circuit breakers and then plummeted in mid-June 2020, which led stock indices around the world to plunge.

Frequent stock market turbulence greatly affects the global economy and financial system. The connectedness among stock markets and the cross-market contagion effect of financial risks at major public events attract much attention from academia and industry. The related research can provide theoretical insights useful for strengthening the connectedness among stock markets, reducing financial risk, and improving investment decisions.

1.2. Literature Review. The international stock market plays an important role in the financial system. One strand of the literature on the connectedness within the international stock market focuses on the transmission between two

important countries [6–10], the connectivity among countries participating in international organizations such as the G7 [11–13], and the dependence between the stock market and other markets, such as exchange markets [14, 15], the crude oil market [16–18], markets for other commodities [19–21], and cryptocurrencies [22–24]. Prior works adopt the GARCH family model, the VAR model, and the Copula model to analyze the time-varying correlations between financial markets, and they emphasize the effects of policy factors (e.g., changes in monetary policy or regime) and national economy factors (e.g., financial and trade linkages) on connectedness among stock markets.

Another strand of the literature performs network analyses of the connectedness among stock markets. Network theory, a powerful tool for investigating financial markets, abstracts the financial system into a network with a set of nodes and edges [25]. This method can be used to analyze stock markets comprehensively and reveal the complexity of the system. The minimum spanning tree (MST), planar maximally filtered graph (PMFG), and correlation threshold method (CTM) are commonly used to construct correlation networks. Mantegna [26] first proposed the MST as a way to analyze the similarities among stock prices in the S&P 500 Index, finding significant implications for portfolio optimization. Since then, the network-based method has been widely adopted to examine connectedness among financial markets. Onnela et al. [27] select 116 stocks in the S&P 500 Index and build a dynamic asset tree based on a correlation matrix of stock price fluctuations, finding that changes in tree length over time are related to investment diversification. Lee et al. [28] present a correlation network of South Korea's stock returns based on the MST method and confirm that the volatility of stock returns is positively correlated with the density of the stock market network. Jung et al. [29], Garas and Argyrakis [30], Tabak et al. [31], and Cheong et al. [32] set up a complex network of stock markets in South Korea, Greece, Brazil, Japan, and China, respectively, based on the MST method and investigated its topological structure.

The PMFG was first proposed by Tumminello et al. [33], as part of the continuous advances in complex network theory and is widely employed in various fields. Tumminello et al. [33] utilize the PMFG to establish a network comprising 300 stocks on the New York Stock Exchange and examine the main topological indicators, such as average path length, node betweenness, and degree. Aste et al. [34] create a network comprising 395 US stocks from 1996 to 2009 based on the PMFG method and find that the 2007 US subprime crisis changed the network's structure and that financial sector stocks were no longer its central nodes.

The CTM is used to explore financial market connections and risk contagion by screening nodes and edges of the original network based on a threshold set to meet the researchers' information retention requirements. Boginski et al. [35] investigate the statistical characteristics of the stock network based on the CTM and conclude that the degree distribution has power-law properties. Huang et al. [36] discover that the network of the Chinese stock market is robust but vulnerable to intentional attacks. Xi and An [37] construct a stock correlation network based on financial indicators to detect the cluster characteristics of the community network; they prove that the independence of the community gradually increases as the threshold rises.

Thus, in contrast to the PMFG and CTM, the MST can filter out a large amount of redundant information and reduce interference. Several scholars point out that the MST method can intuitively and comprehensively identify the transmission mechanism of financial market risk [38]. Therefore, we use the MST model to construct a correlation network with which to study the connectedness of the international stock market and the evolution of the network structure at major public events.

The impact of major public events on the connectedness of the international stock market has caught the attention of scholars because such events trigger frequent turbulence in the financial system. For example, Yang et al. [39] build a jump volatility spillover network of Chinese financial institutions using the VAR model and find that network density reaches a peak during China's stock market disaster of 2015. Huang et al. [40] detect the time-varying comovement among individual stocks in both normal and crisis periods based on a directed weighted stock network and a weighted LeaderRank algorithm; their results demonstrate that network density, the average clustering coefficient, and global efficiency can provide an "early warning" of potential future crises. He et al. [41] use a volatility spillover network to detect the correlation structure of stock markets at past crisis events; they confirm that the network shows a clustering effect when the stock market is impacted by major public events. Cheng et al. [42] investigate how the COVID-19 pandemic has affected the connectedness network of stock market volatility in 19 economies around the world using the Diebold-Yilmaz volatility network model, finding that the outbreak of the COVID-19 pandemic strengthened the overall volatility connectedness and that the global connectedness level remained high throughout 2020.

Nevertheless, research studies on the connectedness of financial markets at major public events have several limitations: (i) First, the connectedness between two stock markets is usually calculated through the Pearson correlation function. The Pearson correlation coefficient (PCC) can only measure the linear connectedness between time sequences; this is a problem because the connectedness between financial markets is nonlinear, complex, and dynamic. Moreover, the PCC does not work well for strongly correlated and nonrandom time series [43], and it is not robust and can be misleading if outliers exist [44] because real-world data are high-level heterogeneous [30, 45]. (ii) Moreover, constructing a connectedness measure requires that the calculated time series maintain the same record length and data synchronization. Obtaining uninterrupted and complete data in stock markets is difficult due to the inconsistencies in trading hours and holidays, which lead to variations in record lengths. To solve this problem, traditional data processing methods have been used to fill and delete data, leading to deviations via data repair. (iii) Additionally, the topology properties of complex financial networks are usually analyzed from a static perspective, such as by selecting specific time points of public events, which ignores the continuity of financial crises and omits

information on the evolution of the network. (iv) Finally, although scholars are increasingly interested in system-level analyses of complex financial networks, few market-level analyses of systemically important markets have been attempted.

Measures of connectedness among network nodes aim to describe and characterize the correlation between two samples or patterns. Among them, dynamic programming (DP) has good robustness [46, 47]. The DTW model is the most representative DP similarity measure, and it can deal with local displacement in the sequence effectively. This model has three significant advantages. First, it can be used to explore the connectedness among return time series with either equal length or unequal length in the international stock market and is thus suitable for the retractable banner. Second, it has superior robustness to the amplitude change, migration, and noise of time series. Third, it is malleable, in contrast to the traditional Euclidean distance. In addition, it is insensitive to abnormal data and truly reproduces the evolution of the international stock market network at major public events. Thus, we utilize the DTW model to examine connectedness in the international stock market. We focus on major public events that have occurred in recent years in order to help authorities formulate regulatory policies and assist investors in predicting future risk changes and formulating related strategies.

1.3. Main Contributions. Our study on the connectedness of the international stock market at major public events has the following contributions.

(i) First, we combine the DTW model with the MST method to remedy the limitations of existing measures.

(ii) Second, we consider different tree lengths, which shed new light on the analysis of systematically important stock markets. We identify the sensitivity of global markets to public event shocks and confirm that the importance of stock markets changes over time.

(iii) Given the complexity of the international stock market network, we study its topology through time-varying analysis. Furthermore, we identify and observe systemically important stock markets based on influence strength.

(iv) We statically and dynamically explore the connectedness of the international stock market at the system, region, and market levels. We consider global efficiency by investigating the systemic connectivity of the network, and we examine the crossregion, within-region, and total connectedness of several geographical regions in order to assess the systematically important stock markets.

1.4. Article Organization. The rest of this article proceeds as follows: In the next section, we explain the DTW model and the evaluation criteria used for network connectedness. In Section 3, we describe our data and perform a preliminary analysis. In Section 4, we evaluate connectedness on three levels (i.e., system, region, and market). Finally, we conclude the article in Section 5.

2. Methodology

2.1. Dynamic Time Warping. We use the dynamic time warping (DTW) model to study a return time series with equal and unequal lengths in the international stock market while dealing with the local displacement, which overcomes the synchronous constraint of the PCC [48]. This model is widely employed in speech recognition and other pattern recognition tasks, such as sign language recognition, gesture recognition, online signature matching, data mining, time series clustering, handwriting, and computer vision. However, few scholars have applied it to finance research [49–51].

After constructing a distance matrix, we utilize dynamic programming to seek the optimal curved path with the smallest cumulative distance to measure the connectedness among stock markets. Supposing that two stock indices' normalized log-returns, R_i and R_j, have the lengths of M and N, respectively, where $R_i = \{R_i(1), R_i(2), \ldots, R_i(m), \ldots, R_i(M)\}$ and $R_j = \{R_j(1), R_j(2), \ldots, R_j(n), \ldots, R_j(N)\}$, we define the local cost matrix C_{ij} for the alignment of two sequences R_i and R_j as follows:

$$C_{ij} = \begin{bmatrix} d\left(R_i(1), R_j(1)\right) & d\left(R_i(1), R_j(2)\right) & \cdots & d\left(R_i(1), R_j(N)\right) \\ d\left(R_i(2), R_j(1)\right) & d\left(R_i(2), R_j(2)\right) & \cdots & d\left(R_i(2), R_j(N)\right) \\ \vdots & \vdots & \ddots & \vdots \\ d\left(R_i(M), R_j(1)\right) & d\left(R_i(M), R_j(2)\right) & \cdots & d\left(R_i(M), R_j(N)\right) \end{bmatrix}, \quad (1)$$

where the (mth, nth) element of the matrix denotes the square distance $d(R_i(m), R_j(n))$ between the two points $R_i(m)$ and $R_j(n)$; thus, $d(R_i(m), R_j(n) = (R_i(m) - R_j(n)^2$.

The warping path is a sequence $p = \{p_1, p_2, \ldots, p_k, \ldots, p_{k+1}\}$ that satisfies the following criteria [52]:

(i) Boundedness: $\max(M, N) \le K \le M + N + 1$

(ii) Boundary condition: $p_1 = (1, 1)$ and $p_k = (M, N)$; they are used to indicate the start and end of a curved path

(iii) Monotonicity condition: $m - m' \ge 0$ and $n - n' \ge 0$

(iv) Continuity: assuming that two adjacent elements $p_{k+1} = (m, n)$ and $p_k = (m', n')$ are on a curved path, there must be $m - m' \leq 1$ and $n - n' \leq 1$; that is, the adjacent elements in the warping path are also adjacent in a local cost matrix

The total cost c_{ij}^p of a warping path p between R_i and R_j with respect to the local cost matrix C_{ij} (all pairwise distances) is defined as follows [52]:

$$c_{ij}^p = \sum_{k=1}^{K} C_{ij}(m_k, n_k), \tag{2}$$

where $C_{ij}(m_k, n_k)$ is the element of the m_kth row and the n_kth column of the local cost matrix C_{ij}.

There are exponentially warping paths that meet the aforementioned conditions, and the connectedness measure D_{ij} between R_i and R_j is the length of optimal warping path p^* that minimizes the warping cost. It is defined as follows:

$$D_{ij} = \frac{1}{K} c_{ij}^{p*}, \tag{3}$$

such that $p* = \{p_1^*, p_2^*, ..., p_k^*, ..., p_K^*\} = \text{argmin}(c_{ij}^p, p \in P^{M\times N})$, where $P^{M\times N}$ is the set of all possible warping paths, and K in the denominator is employed to address the disadvantage that warping paths may have different lengths. If two stock indices, i and j, are entirely similar, then $D_{ij} = 0$; if the two stock indices are completely dissimilar, then $D_{ij} = 1$. Consequently, $0 \leq D_{ij} \leq 1$.

We obtain the similarity matrix (i.e., connectedness matrix) by calculating the connectedness D_{ij} between any two stock markets. Then, the adjacency matrix can be counted based on the similarity matrix.

Finally, the adjacency matrix is converted into the international stock market network by the MST method. Following graph theory, we construct the MST that is a tree structure, by connecting N nodes with $N - 1$ edges. Each stock market corresponds to a node, and the connectedness between two stock markets corresponds to an edge in the network. It is required that the sum of the weights of all edges in the tree be the smallest and that the edges do not form a loop. Thus, MST is utilized to select $N - 1$ edges with the strongest connectedness (i.e., the smallest distance) for each stock market to form a network. Therefore, MST has superior robustness and is the preferred network analysis tool for many scholars.

2.2. Evaluation Criteria for Network Connectedness. We employ specific evaluation criteria for network connectedness to examine the topology of the international stock market.

We first introduce normalized tree length (NTL). Based on the $N \times N$ similarity matrix D, the NTL measure is used to explore the properties of the MST of the international stock market, which is defined as follows [27, 43]:

$$NTL = \frac{1}{N-1} \sum_{D_{ij} \in \Theta} D_{ij}. \tag{4}$$

Similarly, we explore connectedness and information exchange efficiency in the international stock market network using global efficiency (GE), which comprehensively considers the connection efficiency of node pairs. The GE measure is generally defined as follows:

$$GE = \frac{1}{N(N-1)} \sum_{i\neq j \& i,j=1}^{N} \frac{1}{d(i,j)}, \tag{5}$$

where $d(i, j)$ denotes the shortest path length from node i to j and $d(i, j) = +\infty$ if there is no path from i to j in the network.

Regional and sectoral aggregation is widely investigated in [9, 53–58]. Following the region-level connectivity measure proposed by Wang et al. [59], we apply regional distance (RD) and regional connectedness (RC) from one region m to another region n (including itself), which are defined as follows:

$$RD_{m\Leftrightarrow n} = \frac{1}{N_m N_n} \sum_{i=1}^{N_n} \sum_{j=1}^{N_m} D_{ij}, \tag{6}$$

$$RC_{m\Leftrightarrow n} = 1 - RD_{m\Leftrightarrow n}, \tag{7}$$

where N_m and N_n are the number of stock markets in regions m and n, respectively. When $m = n$, $N_n = N_m - 1$, and $i \neq j$.

In equation (6), we standardize the distance between two regions by utilizing their respective numbers of stock markets to eliminate the sample size bias because four regions have different numbers in our sample.

In the network, letting Γ_i be the set of nodes connected to node (i.e., stock market index) i, we define the influence strength (IS) of node i as follows:

$$IS_i = \sum_{j\in\Gamma_i} \rho_{ij}, \tag{8}$$

where ρ_{ij} is the correlation coefficient between node i and j, and the conversion formula between ρ_{ij} and D_{ij} is as follows:

$$\rho_{ij} = 1 - D_{ij}^2. \tag{9}$$

If two stock indices, i and j, are entirely similar, then $\rho_{ij} = 1$; if the two stock indices are completely dissimilar, then $\rho_{ij} = 0$. Consequently, $0 \leq \rho_{ij} \leq 1$.

Therefore, the value of IS depends on two factors: the number of edges connecting the node and the value of the correlation coefficient.

3. Data Description and Preliminary Analysis

3.1. Sample Selection. We select the daily closing prices of 46 important stock market indices from January 23, 2003, to July 16, 2021, provided by the *Wind* database. Our sample comprehensively reflects quotations on the international stock market. Complete data for all 50 stock markets is not available. Hence, the sample includes 46 of the top 50 markets ranked by their average daily trading volumes, which are geographically widespread and account for 90% of international stock market capitalization.

These 46 important stock markets are in four regions: Europe, the Middle East and Africa, America, and the Asia-Pacific region. The location and descriptive statistics of each stock market are shown in tables 1 and 2 (in the Appendix). The average returns of the stock markets were all positive during the sample period, implying that they offer generally good investment value. Additionally, the skewness and kurtosis values show that the return series of the stock markets have a sharp peak and thick tail, reflecting a non-normality of the unconditional distribution of the return time series.

3.2. Data Description. Figure 1 shows the average annual return and the average daily return of the stock market indices from 2003 to 2021. We find that the average annual return changes greatly at public events and drops significantly during the 2008 subprime mortgage crisis (with the lowest value being −0.29%), the 2010-2011 European sovereign debt crisis, the 2013–2015 Fed rate hike and international crude oil plunge, the 2018–2021 period of Sino-US trade friction, and the COVID-19 pandemic. A rebound occurs during a time of financial stability.

There is a close correlation between the average daily return fluctuation and the major public events. The fluctuations, ranging from large to small, correspond to the following events: the US subprime crisis, the COVID-19 pandemic, the Fed rate hike, the Chinese A-share "stock disaster," and the European debt crisis.

Figure 1 also shows that the sample period is split into five periods according to the major public events. In each period, the average annual return declines and rises along with the beginning and ending of the events, and the fluctuations in the average daily return grow from small to large and then decline back to small.

3.3. Subdivision Basis of Sample Period. We examine the impact of public events on the international stock market by dividing the sample period into five subperiods, as described below.

(i) In the first half of 2003, the People's Bank of China, the State Administration of Foreign Exchange, and the relevant financial departments issued a series of policies and regulations on foreign exchange management and overseas investment to adapt to the requirements of the World Trade Organization. As an emerging market economy, China began to integrate into the world financial system. We denote the period before the US subprime crisis (January 2003–June 2007) as Period I.

(ii) Several scholars consider that the US subprime crisis started in June 2007 and ended in June 2009 [43]. We thus denote the period from June 2007 to June 2009 (during the US subprime crisis) as Period II.

(iii) After that crisis, the international financial market entered a recovery phase, and the European debt crisis began, starting in Greece. Larger countries such as France and Germany were affected later. The sovereign rating of France declined from the AAA level in early 2012. Afterward, Ireland became the first Euro Zone country to officially withdraw from the rescue measures on December 15, 2013, meaning that the European debt crisis was greatly eased and temporarily came to an end. We denote the period spanning the global financial crisis recovery and the European debt crisis (June 2009–December 2013) as Period III.

(iv) In the next subperiod, from 2013 to 2018, a series of Black Swan events occurred that had adverse effects

Table 1: Stock market indices and their corresponding regions.

Country	Stock market index	Region
Chile	IPSA	America
Argentina	Merval	America
Ireland	ISEQ	Europe
Austria	ATX	Europe
Australia	AORD	Asia-Pacific
Belgium	BFX	Europe
Denmark	OMX20	Europe
Germany	DAX	Europe
Russia	RTS	Europe
France	CAC40	Europe
Philippines	PSI	Asia-Pacific
Finland	OMX helsinki	Europe
United Kingdom	FTSE 100	Europe
Singapore	STI	Asia-Pacific
South Korea	KS11	Asia-Pacific
Netherlands	AEX	Europe
Canada	GSPTSE	America
Czech	PX	Europe
Luxembourg	LUXX	Europe
Malaysia	KLSE	Asia-Pacific
United States	S&P500	America
Mexico	MXX	America
Norway	OSE	Europe
Portugal	PSI	Europe
Japan	NIKKEI 225	Asia-Pacific
Sweden	OMXSP	Europe
Switzerland	SSMI	Europe
China	SSE	Asia-Pacific
Thailand	SET INDEX	Asia-Pacific
Spain	SMSI	Europe
Greece	ASE	Europe
Hungary	BUX	Europe
Israel	TA100	Middle East and Africa
Italy	FTSEMI	Europe
Indonesia	JKSE	Asia-Pacific
Poland	WIG	Europe
Vietnam	VNINDEX	Asia-Pacific
Iceland	ICEXI	Europe
New Zealand	NZ50	Asia-Pacific
India	SENSEX	Asia-Pacific
Brazil	IBOVESPA	America
Venezuela	IBC	America
Turkey	XU100	Middle East and Africa
Egypt	CASE30	Middle East and Africa
Nigeria	NGSEINDX	Middle East and Africa
Lebanon	BLOM	Middle East and Africa

Table 2: Descriptive statistics of each stock market index.

	Mean	Std. dev	Maximum	Minimum	Skewness	Kurtosis
Chile	0.000414713	0.010738	0.151686	−0.15297	36.52445	−0.47002
Argentina	0.001065713	0.02271	0.139005	−0.47692	58.1052	−2.86732
Ireland	0.000133197	0.013661	0.097331	−0.10416	9.483857	−0.43244
Austria	0.00025793	0.015116	0.12021	−0.1482	11.43452	−0.47025
Australia	0.00021312	0.009936	0.053601	−0.08554	9.811027	−0.60879
Belgium	0.000180872	0.012046	0.09334	−0.09168	9.845512	−0.15525
Denmark	0.000440809	0.012991	0.105853	−0.1923	20.32266	−0.78353
Germany	0.000398554	0.013657	0.107975	−0.1183	9.867267	−0.18562
Russia	0.000365696	0.021759	0.202039	−0.39454	38.62608	−1.65039
France	0.000178934	0.01363	0.105946	−0.11476	10.35057	−0.10197
Philippines	0.000529756	0.012929	0.131324	−0.13089	13.22437	−0.28913
Finland	0.00014869	0.01377	0.088	−0.12302	9.111103	−0.31114
UK Kingdom	0.000187913	0.011284	0.093843	−0.10327	12.60249	−0.23381
Singapore	0.000227348	0.01104	0.088659	−0.10628	11.98931	−0.1961
South Korea	0.000320125	0.01291	0.112844	−0.11172	11.01369	−0.58604
Netherlands	0.000179311	0.01316	0.100283	−0.12614	12.52358	−0.19825
Canada	0.000233094	0.010691	0.093703	−0.16999	29.31364	−1.4559
Czech	0.000208509	0.013616	0.123641	−0.16185	22.66821	−0.98643
Luxembourg	0.000168964	0.01407	0.152926	−0.16734	17.80594	−0.41434
Malaysia	0.000220867	0.007346	0.048869	−0.09979	15.90543	−0.76308
USA	0.000324398	0.011741	0.109572	−0.13777	17.70126	−0.57066
Mexico	0.000506444	0.012196	0.104407	−0.16278	16.89472	−0.49084
Norway	0.000548777	0.014095	0.091881	−0.15667	13.37254	−0.85664
Portugal	0.00018028	0.012294	0.183569	−0.17068	41.85238	−0.7964
Japan	0.000252219	0.015045	0.132346	−0.12715	11.61171	−0.63244
Sweden	0.00038072	0.012643	0.086289	−0.1232	10.05852	−0.33547
Switzerland	0.000218889	0.011052	0.107876	−0.0907	11.11371	−0.25009
China	0.000169464	0.015859	0.090345	−0.09256	7.504331	−0.50661
Thailand	0.000379686	0.012688	0.10577	−0.16063	18.31793	−1.08693
Spain	0.00010038	0.013885	0.137372	−0.13318	11.76595	−0.1321
Greece	−0.00017079	0.020025	0.196712	−0.19138	14.42364	−0.27617
Hungary	0.000436519	0.017229	0.356166	−0.36647	105.1957	−0.25989
Israel	0.000509695	0.089036	3.515917	−3.47592	1510.785	0.639923
Italy	$3.24E-05$	0.014445	0.106593	−0.14051	10.7802	−0.4434
Indonesia	0.000725063	0.013467	0.076231	−0.11306	11.01117	−0.63213
Poland	0.000364452	0.012984	0.176326	−0.20827	31.96476	−0.83331
Vietnam	0.00044173	0.015264	0.19903	−0.19918	20.97501	0.008044
Iceland	$-7.37E-06$	0.021051	0.060572	−1.0622	1697.964	−35.1124
New Zealand	0.000429481	0.006799	0.058146	−0.04938	8.720995	−0.60549
India	0.000641998	0.014345	0.1599	−0.11809	13.53421	−0.19143
Brazil	0.000600427	0.017617	0.136782	−0.18749	11.25471	−0.23355
Venezuela	0.002267143	0.161675	0.431492	−6.90285	1746.56	−40.8986
Turkey	0.000563264	0.019089	0.326883	−0.32566	50.54083	−0.29062
Egypt	0.001076359	0.019534	0.158032	−0.17992	10.36257	−0.51787
Nigeria	0.000184842	0.014365	0.346211	−0.35423	194.774	−0.16724
Lebanon	0.00013838	0.01036	0.084903	−0.10688	22.87406	−0.13297

on the financial system, such as the hike in the US Federal Reserve's interest rate, plummeting crude oil prices, and Brexit. We denote this period of economic recession (December 2013–March 2018) as Period IV.

(v) In March 2018, US President Trump decided to impose punitive tariffs on products imported from China. China responded immediately and announced additional tariffs on $3 billion worth of US goods. The effects of the trade war quickly spread throughout the world. In 2020, the COVID-19 pandemic spread around the world and was a huge shock to the international stock market. We denote the period of Sino-US trade friction and the COVID-19 pandemic (March 2018–July 2021) as Period V.

3.4. Rationale for Subsample and Full-Sample Analysis. Using our sample period subdivision, we explore the structure and topology of the international stock market network by performing subsample and full-sample analyses; these have distinct emphases and advantages.

The subsample analysis conducts an in-depth examination of the international stock market network over five

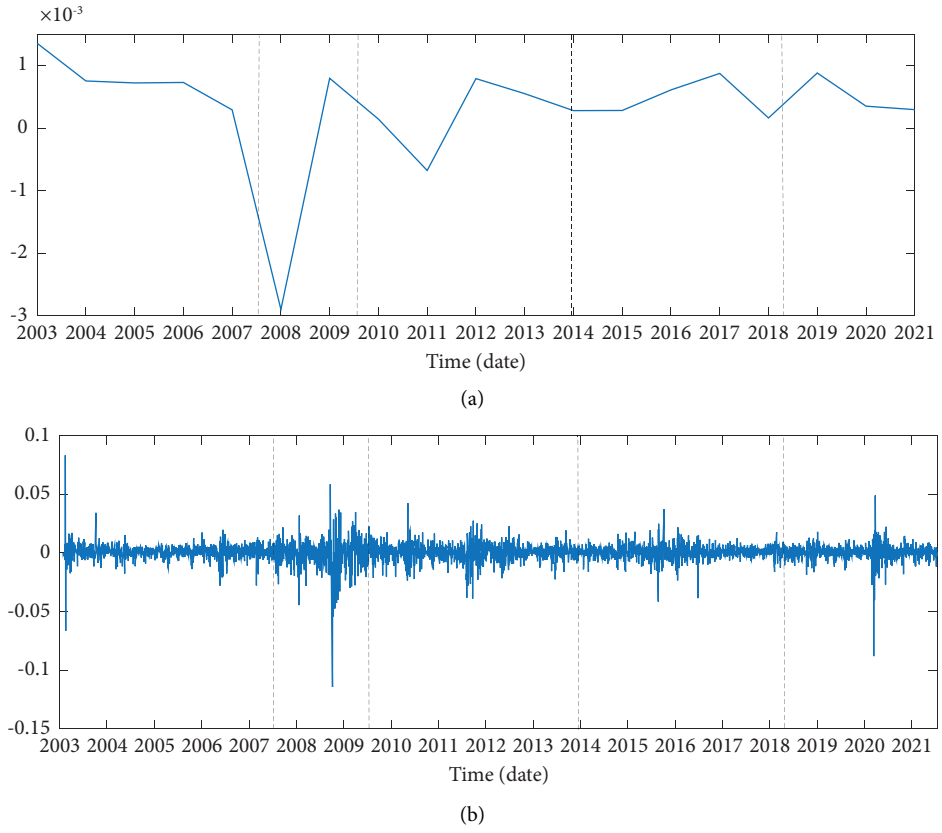

Figure 1: Average return of international stock indices. (a) Average annual return. (b) Average daily return.

periods. Similar to international economic fundamentals, stock market connectedness shows structural and cyclical regularity. The occurrence of major public events leads to variances in the network structure during the sample periods. Thus, the evolution of the connectedness among stock markets over periods of financial crises and stability can be investigated. The subsample analysis focuses on special clusters, links, and nodes from the micro perspective to examine the impact of major public events and the economic fundamentals of various countries.

The full-sample analysis focuses on the overall connectedness and connectivity efficiency of the international stock market network. The full-sample analysis uses the GE index and sliding window method, which can not only explore the topology of the international stock market network but also capture the dynamic impact of major public events from a systemic perspective.

4. Empirical Study

4.1. Construction of the International Stock Market Network. Figures 2–6 show the MSTs of the international stock market in five subperiods. The network consists of four clusters: the European, Middle Eastern, African, Asia-Pacific, and American clusters. In each MST, countries from different geographical regions are indicated in different colors.

4.1.1. Construction of the Network before the US Subprime Crisis. Figure 2 displays the international stock market network of Period I. France from Europe, Indonesia from Asia-Pacific, and Canada from America are the central nodes of their respective clusters. Asia-Pacific and America are divided into several groups.

We find that strong economies in the Asia-Pacific region are separate from their geographic cluster. For example, Japan, South Korea, and Singapore, located in the European cluster, are all Asia-Pacific countries. This result occurs for two reasons. (i) First, Japan and South Korea are economically developed countries with complete financial systems; indeed, Japan is called "ApacExJap" (i.e., "Asia-Pacific region except for Japan"). (ii) Second, the economic growth of Singapore, Japan, and South Korea has been deeply influenced by Western countries, and their financial systems are relatively independent of those of other Asia-Pacific countries.

Meanwhile, breaking away from the America cluster, Brazil enters the edge of the European cluster and becomes a node closely connected with China and Russia. This can be explained as follows: (i) as a BRICS country, Brazil is closely connected to China and Russia, also BRICS members. Thus, their economies are highly complementary, and they engage in close cooperation on energy, trade, agriculture, and food security. (ii) the Brazilian financial market is also highly

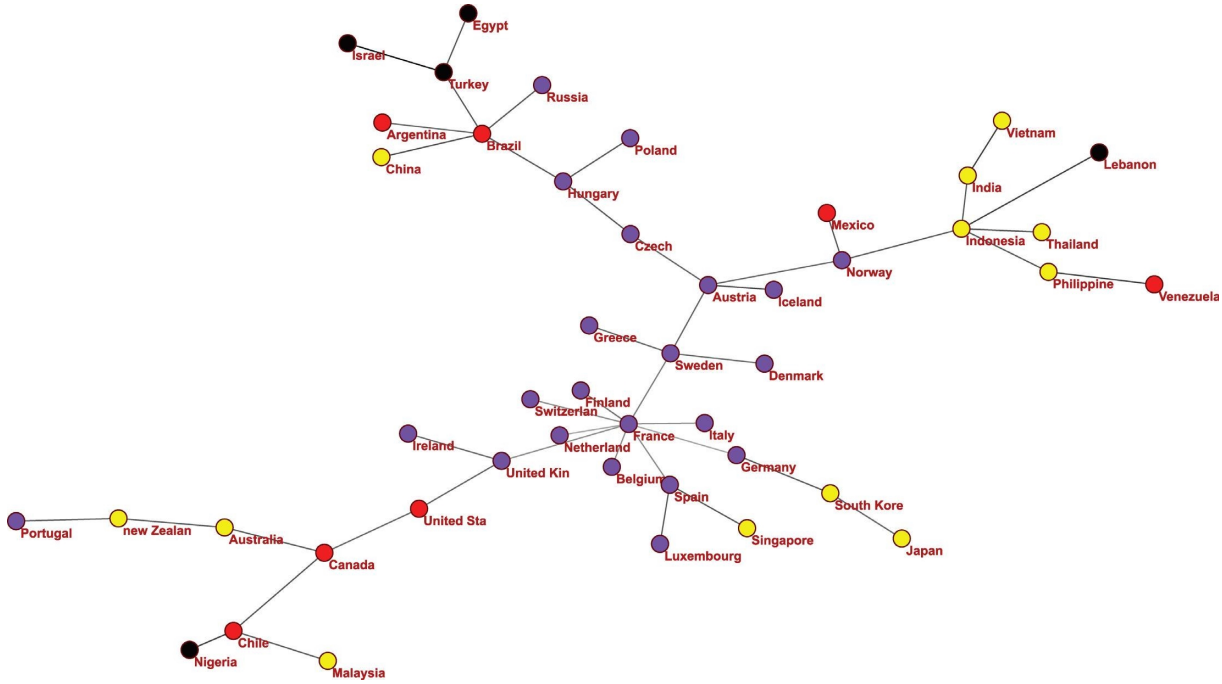

Figure 2: Network of period I, from January 2003 to June 2007. *Note*. Yellow represents Asia-Pacific countries, purple represents European countries, red represents American countries, and black represents Middle Eastern and African countries (the same applies to Figures 3–6).

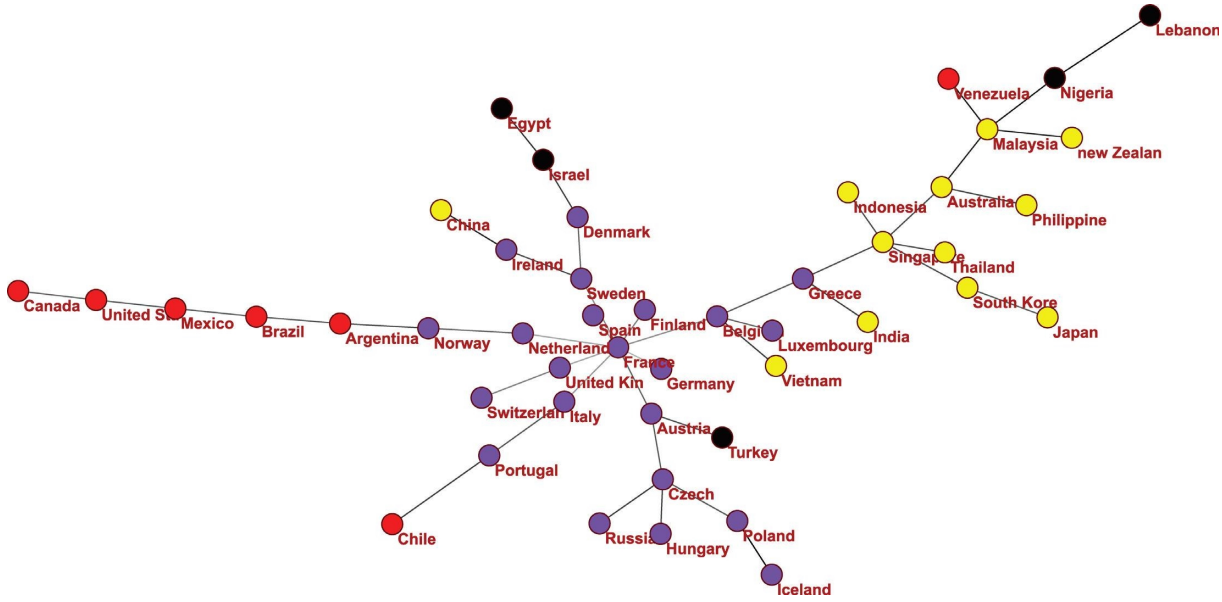

Figure 3: The network of period II, from June 2007 to June 2009.

internationalized. Taking average daily trading volume as the statistical parameter, foreign investors account for more than 40% of Brazil's stock market and derivatives market, and most are from the United States and Europe. The proportion of foreign investor shareholding is higher in the Brazilian stock market than in most other American countries. Furthermore, the Brazilian stock market offers a platform for international product trading. For example, the Brazilian Exchange and the US CME jointly issue cross-linked products.

4.1.2. Construction of the Network during the US Subprime Crisis. The network of Period II differs considerably from that of Period I, as shown in Figure 3. The number of central nodes decreases, and the links in the network become closer. As a result, the network consisting of several clusters can even be regarded as a large, unified cluster. The geographical aggregation effect is more obvious: (i) The Asia-Pacific cluster was concentrated during the US subprime crisis, and its central node is Singapore. (ii) The central node of the European cluster is still France. China is the only country

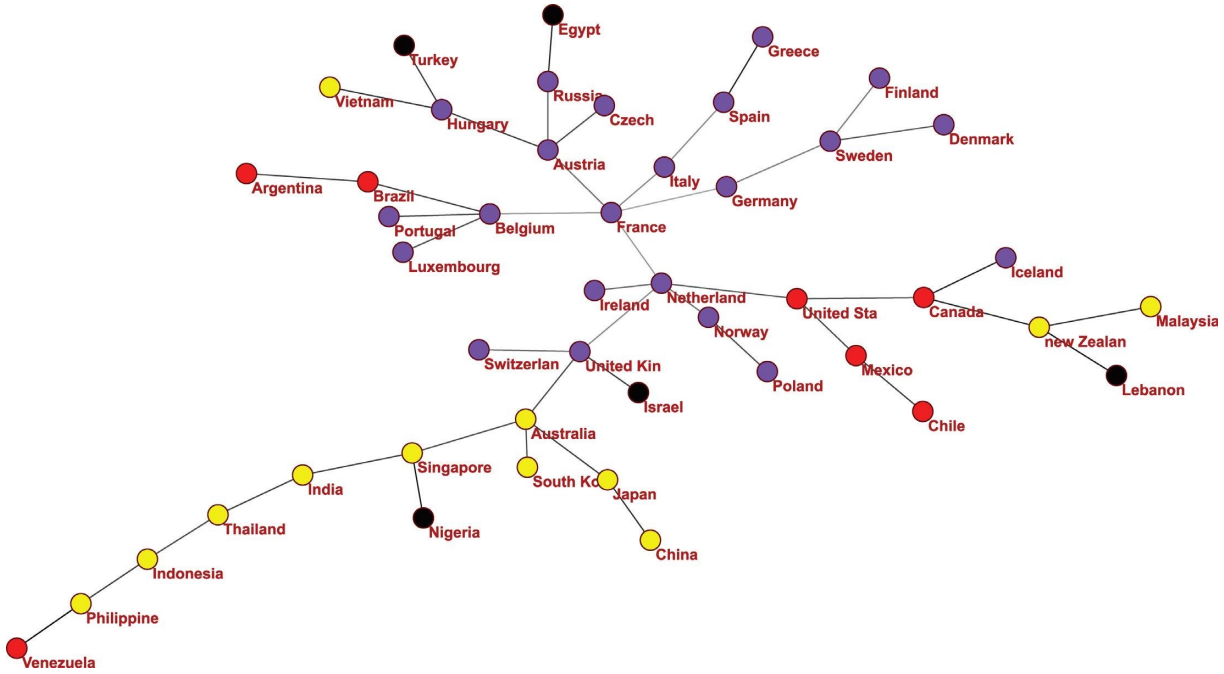

Figure 4: Network of period III, from June 2009 to December 2013.

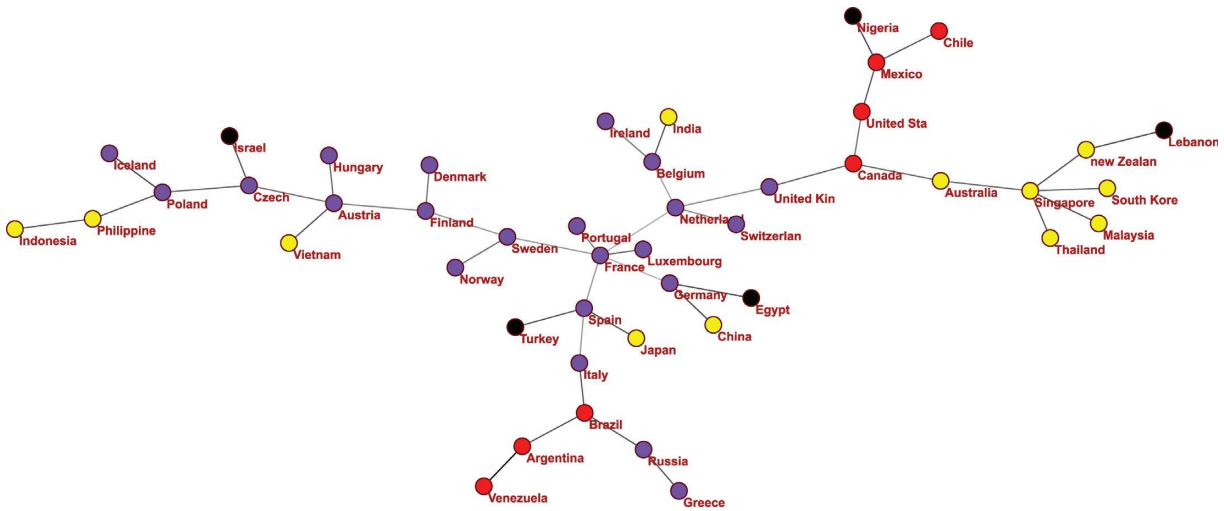

Figure 5: Network of period IV, from December 2013 to March 2018.

that is separated from the Asia-Pacific cluster, and it is directly linked to the European cluster via Ireland and Sweden. Another interesting finding is that China is closer to the center node than it was in Period I, and the Chinese position starts rising in the network.

Figures 2 and 3 show that Singapore is an important node in the Asia-Pacific cluster. As a financial center, Singapore became more prominent during the US subprime crisis. This may happen because its government promotes the development of Singapore as a "financial nation" and seeks to strengthen Singapore's position as an offshore US dollar center and preferred asset management center in Asia. Singapore also has a strong banking system and world-class port logistics. Facing the impact of the Asian financial crisis and US subprime crisis, the Singaporean financial market took effective action under the leadership of its government and continued its development as an international financial center. During the US subprime crisis, Singapore was the only Asian country that was rated AAA by the three major credit rating agencies (i.e., Fitch International, Standard and Poor's, and Moody's).

4.1.3. Construction of the Network during Crisis Recovery and the European Debt Crisis Period. Figure 4 shows the international stock market network in Period III. On the one hand, the closeness of the network is greatly reduced. The European and Asia-Pacific clusters are still centralized. France and the United States become central nodes of the network. Venezuela, Argentina, Lebanon, and other

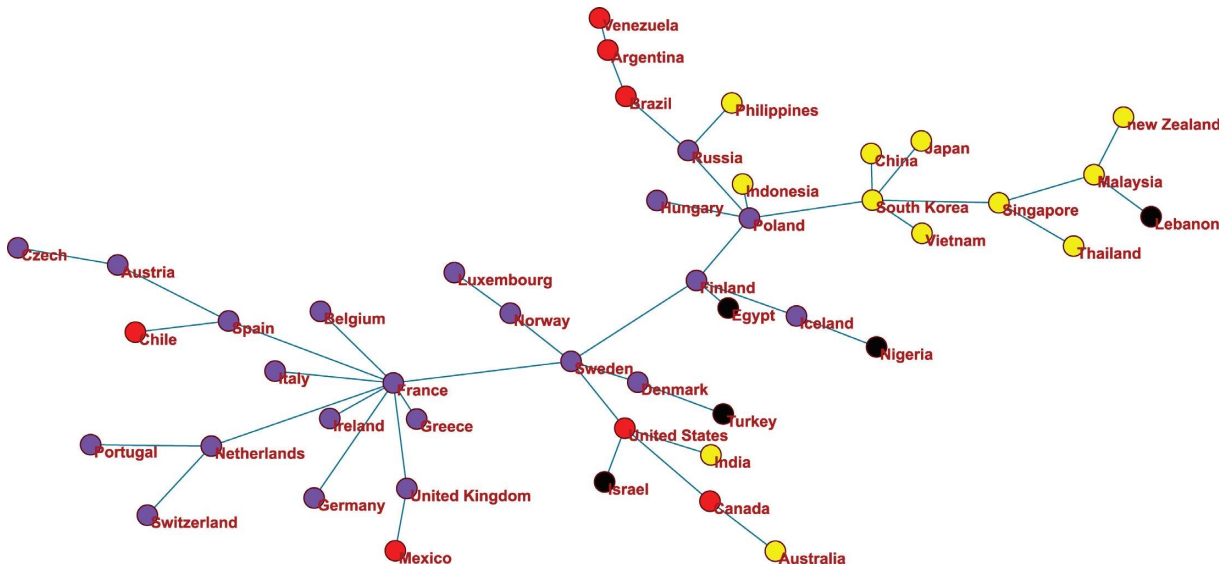

Figure 6: Network of period V, from March 2018 to July 2021.

countries in Latin America, the Middle East, and Africa are on the margins.

By contrast, China is reincorporated into the Asia-Pacific cluster and is connected to the European cluster through the United Kingdom, Japan, and Australia, which all have relatively close financial and trade links to China. The Asia-Pacific cluster is still clustered with Singapore as the central node. Simultaneously, the American cluster is divided into two parts: one is composed of developed countries in North America, which are closely linked to the European cluster via the United States; the other is comprised mainly of Latin American countries, on the margins of the network.

4.1.4. Construction of the Network during the Global Economic Recession. Figure 5 shows the international stock market network during the global economic recession. From a macro perspective, the network structure is closer than it was in Period III due to the hike in the US Federal Reserve's interest rate, the plunge in international crude oil, and China's A-share stock disaster. Aside from France, the Netherlands, Finland, and Belgium become central nodes of the network. The American cluster contains two parts: developed countries in North America and underdeveloped countries in Latin America. Moreover, the Asia-Pacific cluster no longer exists and is divided into several parts. China is linked to France via Germany. China's influence on the international stock market increases significantly due to the progress of the "Belt and Road" initiative.

4.1.5. Construction of the Network during the Sino-US Trade Friction and COVID-19 Pandemic Period. Figure 6 shows the MST during the time of Sino-US trade friction and the COVID-19 pandemic. The geographical aggregation greatly diminishes. Except for the European and Asia-Pacific clusters, which are still centralized, the other clusters no longer exist. Korea is connected to China, Japan, Singapore, and Vietnam, which highlights its important position. India and Australia are separated from the original Asia-Pacific cluster and are connected to the United States and Canada in the America cluster. Note that the United States and Canada are connected to the European cluster, while most other American countries are on the margins of the network.

4.1.6. General Features of Network. The international stock market network has noteworthy features in all periods.

(i) The stock markets are closely linked and move towards geographical aggregation in the following way: first, European markets exhibit the most obvious aggregation, and the European cluster occupies the core position of the network in all periods. Second, the American and Asia-Pacific clusters are located around the European cluster, which forms the international stock market network. Third, the Asia-Pacific cluster exerts a weak influence on the stock markets of other regions. Similarly, the Middle Eastern and African cluster is marginalized in the international stock market network.

(ii) The strong connectedness within every cluster confirms the significant geographical aggregation effect. The connectedness among stock markets in the same region is stronger than that among stock markets in different regions. This feature is more evident in the European cluster than in the others.

(iii) The structure of the international stock market network varies over time, and each cluster has a relatively fixed central node. In the European cluster, France is located in the center, and it exerts a significant influence on the European cluster and the entire network in the sample period. Singapore is the central node of the Asia-Pacific cluster, and the United States is the central node of the

American cluster. The Middle Eastern and African cluster has no central node because of its marginal position in the network.

(iv) A country's position in the network is closely related to its economic and financial development, and the distances between nodes reflect the financial connections between the countries. Developed countries are relatively concentrated and closely linked, while developing countries are on the margins of the network. It is worth noting that the connectedness of the international stock market increases markedly during major public events, indicating that financial crises are contagious.

4.2. System-Level Connectedness. We investigate the systemic connectedness of the international stock market at public events by combining the DTW-based network with the full-sample analysis and using GE as the statistical index. We also adopt the sliding window method to determine the time-varying property of GE. Following Liu and Wan's [60] judgment regarding time window width, we use a longer time window width in order to capture the long-term trend of the international stock market accurately. A shorter time window width should be used to analyze the short-term dynamic impacts of financial crises, economic cycles, and seasonal factors on stock markets. Following Liu and Wan [61], we set the time window width at 250 trading days (approximately one year) and the step length at five trading days (one week).

As shown in Figure 7, the GE of the international stock market network fluctuates in a range of [0.06, 0.08] during the sample period. In Period I, the GE maintains a low level, from 0.062 to 0.071, because the international stock market is stable. In Period II, the GE soars and reaches its peak value at the end of 2008. Afterward, it gradually declines and returns to a normal value by the end of the US subprime crisis in 2009. During Period III, the GE declines but then increases relatively rapidly in mid-2011. During Period IV, the GE rises and then falls, declining to its lowest value at the beginning of 2018. During Period V, the GE once again presents an upward trend and reaches its second-highest peak in 2020 during the COVID-19 pandemic.

Thus, the sharp increase in GE occurs in four of the five periods, which correspond to the following public events: (i) the US subprime crisis from 2007 to 2009; (ii) the European debt crisis in 2011; (iii) the US Fed's first interest rate hike in 10 years and China's A-share stock disaster in 2015; and (iv) the period of Sino–US trade friction in 2018 and the COVID-19 pandemic in 2020. By contrast, the GE remains low with small fluctuations during Period I and other periods when no major public events occur. We find that public events exacerbate the volatility of stock markets at a certain stage and strengthen their linkages, which increase aggregation in the network and cause GE to reach its peak.

In terms of change amplitude, the most violent increase in GE happened during the US subprime crisis, followed by the world economic recession triggered by the hike in the US Federal Reserve's interest rate, the Chinese A-share stock disaster, and, finally, the European debt crisis. Among these, the European debt crisis imposes a significant impact on Europe but has limited global spread. Therefore, global public events (such as the US subprime crisis) exert a much greater impact on stock markets than do regional public events (such as the European debt crisis).

4.3. Region-Level Connectedness. The stock markets cluster in each of the regions. Following Wang et al. [59], we propose a measure of regional connectedness, shown in equations (6) and (7), to explore the commonly found geographical aggregation (the regional clustering effect in our case) in the international stock market. Table 3 displays the estimations of regional connectedness, where the connectedness between one region and all others (total connectedness) is equal to the corresponding off-diagonal row sums (or column sums). The within-region connectedness (diagonal elements) is significantly stronger than the cross-region connectedness (off-diagonal elements), with the exception of that between the Middle East & Africa and America. The major reason why these two regions have high connectedness is the frequent oil trade between the United States and Middle Eastern countries.

We find that the stock markets of 22 countries in Europe are highly interconnected. By contrast, the Middle East and Africa have the lowest within-region connectedness, indicating a weak influence on the international stock market. Furthermore, the American, Middle Eastern, & African regions are the two highest in terms of total connectedness, manifesting the powerful influence of the US dollar and oil exports. Europe and Asia-Pacific show the third and fourth highest total connectedness levels, respectively. Although Japan and Singapore exert a strong influence on the network, most Asia-Pacific countries are emerging markets with weak influence. Thus, the total connectedness of this region is not high.

4.4. Market-Level Connectedness

4.4.1. Assessment of Systemically Important Stock Markets. Risk contagion speeds and intensities differ among the nodes in the international stock market network when a public event breaks out. Based on the scale, relevance, and globality of the systemically important stock markets, we conduct a comprehensive assessment of risk contagion speed and intensity to analyze their influence.

The measure of risk contagion speed is defined as the number of stock markets infected by the source of risk (a single stock market) within a certain time. The degree of a node is defined as the number of edges directly connected to it, which can be used to represent risk and contagion speed. We can also measure the intensity of risk contagion by calculating the connectedness between one stock market and other stock markets that are connected to it in the network.

We select the IS index, which considers the degree of a node and the weight of the edges (the correlation coefficient between stock markets), to examine the influence of

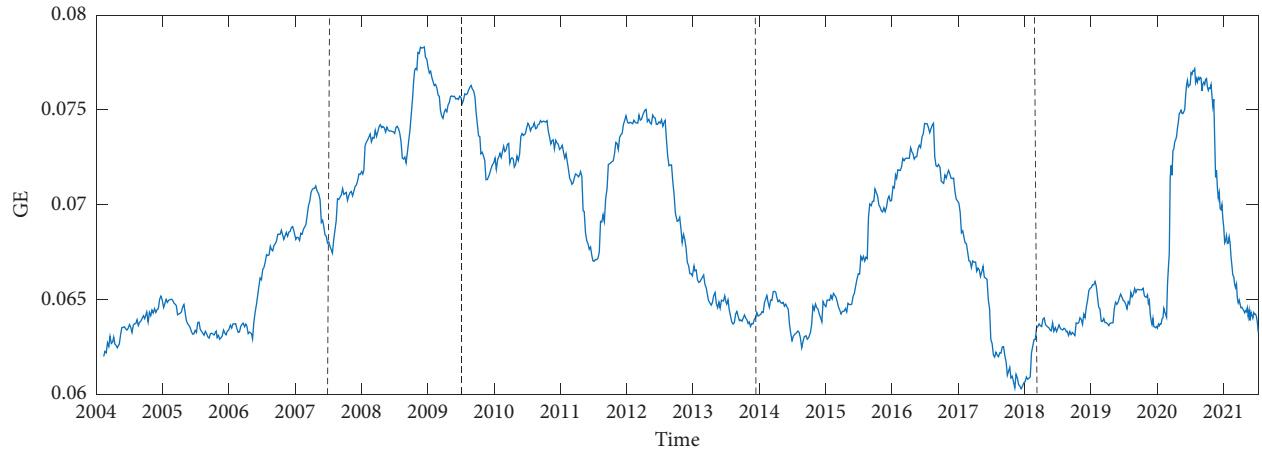

Figure 7: Time-varying global efficiency of the international stock market network.

Table 3: Regional connectedness.

	Europe	Asia-Pacific	Middle East and Africa	America	Total connectedness
Europe	0.8207	0.7336	0.5653	0.7689	2.0678
Asia-Pacific	0.7336	0.7937	0.5792	0.7829	2.0957
Middle East and Africa	0.5653	0.5792	0.7596	0.9679	2.1124
America	0.7689	0.7829	0.9679	0.7667	2.5167

Note. Indicators in the table are normalized as in equations (6) and (7) to eliminate the sample size bias arising because the numbers of countries differ across the four regions.

the stock markets. The greater the IS of a stock market, the stronger its effects on the international stock market network.

We calculate the IS of each node to identify the systemically important stock markets and analyze their network structure over different time periods. The top five nodes in each period are shown in Table 4. At public events, the top five nodes of the network are different across the five periods. The IS in Period I with no public events is significantly lower than that in Period II. Furthermore, Periods III, IV, and V correspond to the European debt crisis, the hike in the US Federal Reserve's interest rate, and the period of Sino-US trade friction, and the COVID-19 pandemic, respectively. The harm of these events is less intense than that of the US subprime crisis. Therefore, the IS in the latter three periods is higher than that in Period I and lower than that in Period II. This indicates that public events make the international stock market network more compact and the IS accordingly higher, which matches the conclusion drawn from the time-varying GE curve.

Meanwhile, we find that the top five nodes based on IS in all periods are all from the European cluster, which coincides with the powerful influence of Europe. Consistent with the outcomes shown in Figures 2–6, the European cluster is in the center of the international stock market network, and it dominates the other nodes and clusters. France is in the top five nodes in all periods and is extremely important in the network. Moreover, the United Kingdom entered the top five during the US subprime crisis. Afterwards, it declines and withdraws from the top five; thus, the leading position of the United Kingdom is highlighted during this period. The Netherlands ranks among the top five nodes in four of the five periods and is especially high in Periods III and IV, reflecting its significant influence. Germany, Sweden, Belgium, Switzerland, and Spain are also among the top five nodes in the five periods, which demonstrates that these countries significantly affect the international stock market.

Taken together, these results show that, first, the international stock market is greatly impacted by France and that Europe is the most important cluster in the network. This result occurs for two reasons. Europe's economy and finance are exceedingly integrated within the European Union, and stock markets in Europe have strong internal connectedness and thus have a significant influence on the stock markets of other regions. Second, the United States and Singapore have the highest IS in the American and Asia-Pacific clusters, respectively, because the United States is the world's largest economy and holds an extremely important position in the international financial market, and Singapore is the financial center of Asia. Third, Japan's IS exceeded Singapore's during the global economic recession, and it is prominent in the Asian financial market. Thus, Singapore and Japan are the most influential nodes in the Asia-Pacific region.

4.4.2. Analysis of Systemically Important Stock Markets. The findings show that France, the United States, and Singapore/Japan are the most systemically important stock markets in their respective regions. China is the world's

Table 4: Top 5 stock markets in international stock market network ranked by IS.

	Country	IS
Period I	France	38.91
	Sweden	38.88
	Switzerland	38.63
	Germany	38.62
	Spain	38.58
Period II	France	40.48
	Sweden	40.36
	Belgium	40.36
	UK	40.30
	Netherlands	40.27
Period III	Netherlands	39.92
	Belgium	39.85
	UK	39.67
	Germany	39.62
	France	39.59
Period IV	Netherlands	39.33
	Finland	39.28
	Belgium	39.27
	France	39.24
	Sweden	39.19
Period V	France	39.53
	Finland	39.46
	Sweden	39.45
	Netherlands	39.43
	Belgium	39.39

second-largest economy and has a growing influence on the international financial system. Thus, we next explore the importance of these markets in the international stock market network. The importance index we select is the tree length, which is the shortest distance when one stock market merges into the MST. We obtain it by calculating the connectedness between the node and its neighboring nodes in the network. We take the average importance indicator of the international stock market as a baseline. The normalized tree length (NTL) can be used to measure the average distance among nodes in order to explore the overall connectedness strength of the international stock market after redundant relationships are "filtered out."

As mentioned, we adopt the sliding window method to detect the time-varying property of the tree length and set the sliding time window width to 250 trading days. To measure market importance in the network, we calculate the time-varying NTL as well as the FRTL, USTL, SGTL, JPTL, and CNTL, as shown in Figure 8. We conclude that their stock markets are more important than the average level in the network if the tree lengths are below the NTL; otherwise, their stock markets are less important.

(i) The average NTL for the full-sample period is 0.3355, and the values in the five periods are 0.3462, 0.3142, 0.4301, 0.3431, and 0.3385, respectively. Since 2004, the NTL curve has fluctuated around 0.35 in a relatively high position. Affected by the US subprime crisis, it shows a downward trend during Period II from 0.3309 to 0.3084. Afterward, the NTL in Period III rises because the global financial environment is resurgent at the end of the US subprime crisis. It displays a short-term decline in 2012 and quickly recovers due to the European debt crisis. Then, the NTL first descends and then rises from 2015 to 2016 because several Black Swan events in the international financial system, such as the US Fed's first rise in interest rates in a decade, the plummeting crude oil price, Brexit, and the Chinese stock market disaster, run through Period IV. Furthermore, the NTL declines slightly during the period of Sino–US trade friction in 2018, and it falls sharply after the COVID-19 outbreak. Next, it rises again in late 2020 and early 2021 as the COVID-19 epidemic is gradually brought under control. In general, the NTL during the sample period experiences three falling/rising cycles.

(ii) The FRTL is the lowest, and its fluctuation range is the largest among all five tree lengths. As the core of the European cluster, France is much more important than the average level of the international stock market. Furthermore, the FRTL is low during public events, indicating that France is highly sensitive to them. It is noteworthy that the importance of France rose fastest from mid-2014 to the end of 2015, and the range of this increase was more dramatic than that of the average importance level.

(iii) The USTL is the closest to the NTL, but its fluctuation range is greater than the NTL's. The USTL is also highly sensitive to public events, and its sharp decline occurred during the US subprime crisis and the Sino-US trade friction period. By contrast, the emergence of the European debt crisis in 2012 and the hike in the Federal Reserve's interest rate in 2016 triggered only a small drop, which indicates that the connectedness between the United States and other markets is only weakly influenced by these events. Furthermore, the US subprime crisis in 2007 and the period of Sino-US trade friction in 2018 exhibit a significant influence on the importance of the United States. As the birthplace of these public events, the United States is obviously greatly affected by them.

(iv) The JPTL and SGTL are exceedingly close, and both are slightly higher than the NTL; this happens because Japan and Singapore have similar importance levels, and these are lower than the average. The fluctuation of the JPTL during the European debt crisis is greater than that of the SGTL, indicating that the Japanese stock market is more sensitive to the European debt crisis than are other markets.

(v) The CNTL is much higher than the NTL, and it fluctuates within a small range after the US subprime crisis. In addition, the importance of China is lower than the average level, and its sensitivity to public events is weaker than that of other

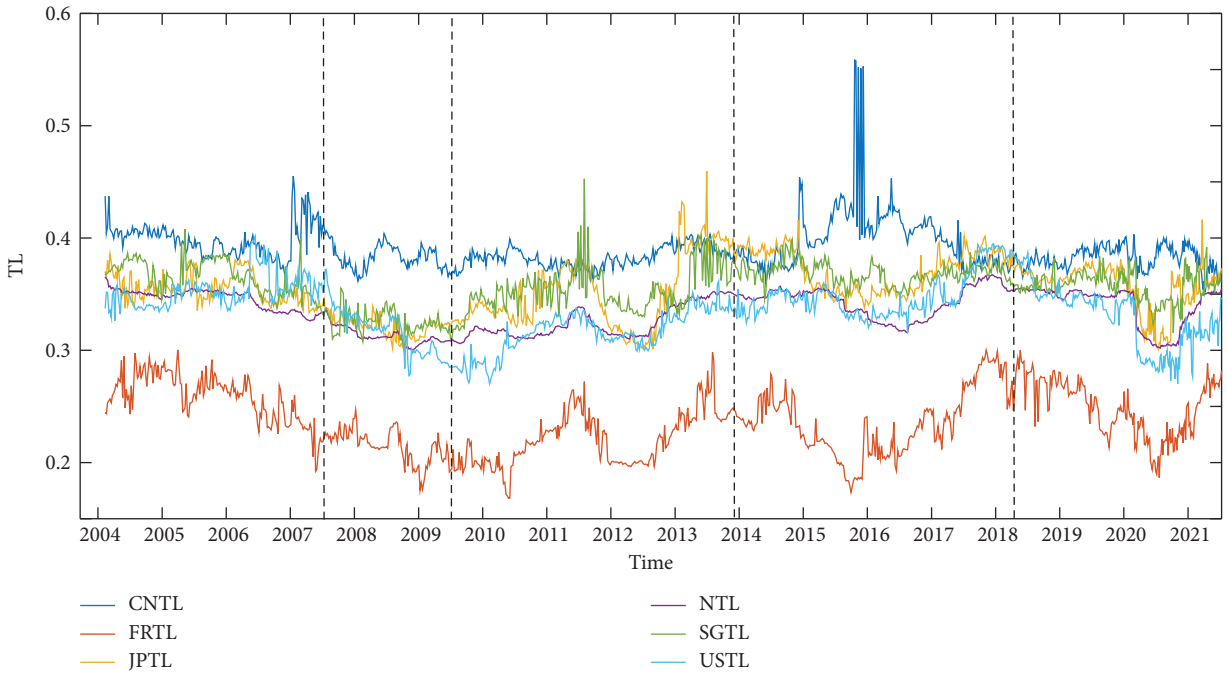

Figure 8: Tree lengths of systemically important stock markets. *Note*. NTL represents the normalized tree length of the international stock market network, and FRTL, USTL, SGTL, JPTL, and CNTL represent the tree lengths of France, the United States, Singapore, Japan, and China, respectively.

systemically important stock markets. It is worth noting that the gap between the CNTL and NTL was widest during the US subprime crisis. Thus, the importance of China is lower during the US subprime crisis than in other periods, which minimizes the extent of economic recession and the risk of contagion during the crisis. The Belt and Road Initiative also has a profound impact on the CNTL. During its implementation in 2015, the CNTL deviates from the NTL and declines; it approaches the NTL after the period of Sino-US trade friction. At that time, the importance of China reaches its peak. The world's two largest economies, China and the United States, are in conflict, which may continue to increase the China's importance. Moreover, the CNTL becomes relatively stable after the COVID-19 pandemic instead of declining sharply, as in other countries. One major reason for this is that China controls the risk of contagion caused by the COVID-19 pandemic effectively through its strong epidemic prevention measures.

5. Conclusions

We build correlation networks using the DTW model and investigate the connectedness of the international stock market at public events at the system, region, and market levels.

(i) At the systemic level, the public events increase market volatility and synergies among the stock markets. During times of stability, the network is relatively loose, and the connectedness among nodes is weak. By contrast, the network becomes integrated and compact after public events, indicating that a sharp increase in network connectedness may signal the emergence of financial crises. Additionally, the GE during the US subprime crisis was significantly higher than it was during the European debt crisis, indicating that global events have a greater impact on network connectedness than regional events have.

(ii) At the regional level, Europe always occupies a core position in the network. Affected by strong within-region connectedness, the network structure shows geographic regionalization. Stock markets in Europe are the most interconnected because of the integration of European finance and economy. Contrariwise, stock markets in the Middle East and Africa have the lowest within-region connectedness, due to their chaotic political situations and backward financial systems. America, the Middle East, and Africa are top-ranked in terms of total connectedness manifesting the powerful influence of the US dollar and oil exports. Europe and Asia-Pacific are ranked lowest in terms of total connectedness.

(iii) At the market level, France, the United States, and Singapore/Japan are the systemically most important stock markets in their respective regions. In particular, France exhibits the strongest influence in all five periods. Moreover, the influence of China increases rapidly, reaching its peak during the period of Sino-US trade friction, which shows that

public events exert an important impact on the countries involved and that the dominance of the international financial system by European and American countries is changing.

Our research studies offer insights useful for investment strategies and systemic risk warning measures for the international stock market, while also providing regulatory authorities with important suggestions regarding financial supervision.

(i) Considering the periodicity of risk contagion among stock markets, governments need to make discretionary choices regarding risk sources, event processes, and categories (i.e., global vs. regional events). Public events are most intense in their early stages, which is often accompanied by a dramatic increase in stock market connectedness. During this stage, authorities should implement policies designed to strengthen bailout efforts, control market liquidity, curb capital outflow, and stabilize investor sentiment.

(ii) Investors should pay more attention to the European stock market, especially the French stock market, when making investment decisions, given the significant influence of Europe in the international stock market network. China's influence on the international stock market has been rising since the Belt and Road initiative began in 2015. It reached its peak during the period of Sino-US trade friction and the COVID-19 pandemic. As the world's largest emerging stock market, China is having an increasingly significant impact on other stock markets due to its openness.

(iii) Amid the increasing risks in the international financial system, authorities should implement rescue policies to reduce the breadth and depth of public events in consideration of the regional clustering effect. Since within-region connectedness is higher than cross-region connectedness in most instances, all countries should pay more attention to the stock markets in their own region, especially those that are systemically important. Stock markets with high IS rankings should also be taken seriously. Additionally, as the Middle East and Africa was closely linked with America, countries in these two regions should focus on their connectedness to prevent financial risks. For example, the Middle Eastern and African countries should be cautious about financial risks coming from America, particularly the United States, whose stock market is systemically important.

Data Availability

The data on the closing prices of stock market indices used to support the findings of this study were supplied by the Wind database under license and requests for access to these data should be made to Wind (https://www.wind.com.cn/).

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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References

[1] D. Acemoglu, A. Ozdaglar, and A. Tahbaz-Salehi, "Systemic risk and stability in financial networks," *The American Economic Review*, vol. 105, no. 2, pp. 564–608, 2015.

[2] P. Gai and S. Kapadia, "Contagion in financial networks," *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 466, no. 2120, pp. 2401–2423, 2010.

[3] P. Caraiani and B. J. Eshel, "Using complex networks to characterize international business cycles," *PLoS One*, vol. 8, no. 3, Article ID e58109, 2013.

[4] K. E. Lee, J. W. Lee, and B. H. Hong, "Complex networks in a stock market," *Computer Physics Communications*, vol. 177, no. 1-2, p. 186, 2007.

[5] A. Nobi, S. Lee, D. H. Kim, and J. W. Lee, "Correlation and network topologies in global and local stock indices," *Physics Letters A*, vol. 378, no. 34, pp. 2482–2489, 2014.

[6] X. M. Li and L. Peng, "US economic policy uncertainty and co-movements between Chinese and US stock markets," *Economic Modelling*, vol. 61, pp. 27–39, 2017.

[7] L. Li, "Daily stock index return for the Canadian, UK, and US equity markets, compiled by Morgan Stanley Capital International, obtained from Datastream," *Data in Brief*, vol. 16, pp. 947–949, 2018.

[8] G. Cao, M. Zhang, and Q. Li, "Volatility-constrained multifractal detrended cross-correlation analysis: cross-correlation among Mainland China, US, and Hong Kong stock markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 472, pp. 67–76, 2017.

[9] J. Li, Y. Shi, and G. Cao, "Topology structure based on detrended cross-correlation coefficient of exchange rate network of the belt and road countries," *Physica A: Statistical Mechanics and Its Applications*, vol. 509, pp. 1140–1151, 2018.

[10] W. Liu, D. Yi, and J. Sui, "Macro-economic factors and co-movement of China's and US stock market," *Journal of Central South University*, vol. 21, no. 4, pp. 105–112, 2015.

[11] O. Tilfani, P. J. Ferreira, and M. Y. El Boukfaoui, "Dynamic cross-correlation and dynamic contagion of stock markets: a sliding windows approach with the DCCA correlation coefficient," *Empirical Economics*, vol. 60, no. 3, pp. 1127–1156, 2021.

[12] E. Baumöhl, "Stock market integration between the CEE-4 and the G7 markets: asymmetric DCC and smooth transition approach," University Library of Munich, Munich, Germany, MPRA Working Paper 43834, 2013.

[13] A. Suurlaht, *Correlation Dynamics in the G7 Stock Markets*, Michael Smurfit Graduate Business School, University College Dublin, Dublin, Ireland, 2016.

[14] G. Boako and P. Alagidede, "Currency price risk and stock market returns in Africa: dependence and downside spillover

effects with stochastic copulas," *Journal of Multinational Financial Management*, vol. 41, pp. 92–114, 2017.

[15] S. Kumar, A. K. Tiwari, Y. Chauhan, and Q. Ji, "Dependence structure between the BRICS foreign exchange and stock markets using the dependence-switching copula approach," *International Review of Financial Analysis*, vol. 63, pp. 273–284, 2019.

[16] C. Conrad, K. Loch, and D. Rittler, "On the macroeconomic determinants of long-term volatilities and correlations in U.S. stock and crude oil markets," *Journal of Empirical Finance*, vol. 29, pp. 26–40, 2014.

[17] R. Boldanov, S. Degiannakis, and G. Filis, "Time-varying correlation between oil and stock market volatilities: evidence from oil-importing and oil-exporting countries," *International Review of Financial Analysis*, vol. 48, pp. 209–220, 2016.

[18] M. Khurshid and B. Kirkulak-Uludag, "Shock and volatility spillovers between oil and emerging seven stock markets," *International Journal of Energy Sector Management*, vol. 15, no. 5, pp. 933–948, 2021.

[19] İ Civcir and U. Akkoç, "Dynamic volatility linkages and hedging between commodities and sectoral stock returns in Turkey: evidence from SVAR-cDCC-GARCH model," *International Journal of Finance and Economics*, vol. 26, no. 2, pp. 1978–1992, 2021.

[20] I. Badshah, R. Demirer, and M. T. Suleman, "The effect of economic policy uncertainty on stock-commodity correlations and its implications on optimal hedging," *Energy Economics*, vol. 84, Article ID 104553, 2019.

[21] T. Chebbi and A. Derbali, "A dynamic conditional correlation between commodities and the Islamic stock market," *The Journal of Energy Markets*, vol. 9, no. 1, pp. 65–90, 2016.

[22] S. Mukherji, "Empirical evidence on bitcoin returns and portfolio value," *The International Journal of Business and Finance Research*, vol. 13, no. 2, pp. 71–81, 2019.

[23] M. Umar, N. T. Hung, S. Chen, A. Iqbal, and K. Jebran, "Are stock markets and cryptocurrencies connected?" *Singapore Economic Review*, pp. 1–16, 2020.

[24] L. A. Gil-Alana, E. J. A. Abakah, and M. F. R. Rojo, "Cryptocurrencies and stock market indices. Are they related?" *Research in International Business and Finance*, vol. 51, Article ID 101063, 2020.

[25] G. J. Wang, C. Xie, and H. E. Stanley, "Correlation structure and evolution of world stock markets: evidence from Pearson and partial correlation-based networks," *Computational Economics*, vol. 51, no. 3, pp. 607–635, 2018.

[26] R. N. Mantegna, "Hierarchical structure in financial markets," *The European Physical Journal B*, vol. 11, no. 1, pp. 193–197, 1999.

[27] J. P. Onnela, A. Chakraborti, K. Kaski, J. Kertesz, and A. Kanto, "Dynamics of market correlations: taxonomy and portfolio analysis," *Physical Review*, vol. 68, no. 5, Article ID 056110, 2003.

[28] J. Lee, J. Youn, and W. Chang, "Intraday volatility and network topological properties in the Korean stock market," *Physica A: Statistical Mechanics and Its Applications*, vol. 391, no. 4, pp. 1354–1360, 2012.

[29] W.-S. Jung, S. Chae, J.-S. Yang, and H.-T. Moon, "Characteristics of the Korean stock market correlations," *Physica A: Statistical Mechanics and Its Applications*, vol. 361, no. 1, pp. 263–271, 2006.

[30] A. Garas and P. Argyrakis, "Correlation study of the Athens stock exchange," *Physica A: Statistical Mechanics and Its Applications*, vol. 380, pp. 399–410, 2007.

[31] B. M. Tabak, T. R. Serra, and D. O. Cajueiro, "Topological properties of stock market networks: the case of Brazil," *Physica A: Statistical Mechanics and Its Applications*, vol. 389, no. 16, pp. 3240–3249, 2010.

[32] S. A. Cheong, R. P. Fornia, G. H. T. Lee et al., "The Japanese economy in crises: a time series segmentation study," *Economics*, vol. 6, pp. 1–81, 2012.

[33] M. Tumminello, T. Aste, T. Di Matteo, and R. N. Mantegna, "A tool for filtering information in complex systems," *Proceedings of the National Academy of Sciences*, vol. 102, no. 30, Article ID 10421, 2005.

[34] T. Aste, W. Shaw, and T. D. Matteo, "Correlation structure and dynamics in volatile markets," *New Journal of Physics*, vol. 12, no. 8, Article ID 085009, 2010.

[35] V. Boginski, S. Butenko, and P. M. Pardalos, "Statistical analysis of financial networks," *Computational Statistics and Data Analysis*, vol. 48, no. 2, pp. 431–443, 2005.

[36] W.-Q. Huang, X.-T. Zhuang, and S. Yao, "A network analysis of the Chinese stock market," *Physica A: Statistical Mechanics and Its Applications*, vol. 388, no. 14, pp. 2956–2964, 2009.

[37] X. Xi and H. An, "Research on energy stock market associated network structure based on financial indicators," *Physica A: Statistical Mechanics and Its Applications*, vol. 490, pp. 1309–1323, 2018.

[38] G. J. Wang and C. Xie, "Correlation structure and dynamics of international real estate securities markets: a network perspective," *Physica A: Statistical Mechanics and Its Applications*, vol. 424, pp. 176–193, 2015.

[39] X. Yang, S. Chen, H. Liu, X. Yang, and C. Huang, "Jump volatility spillover network based measurement of systemic importance of Chinese financial institutions," *International Journal of Finance and Economics*, 2021.

[40] C. Huang, Y. Deng, X. Yang, J. Cao, and X. Yang, "A network perspective of comovement and structural change: evidence from the Chinese stock market," *International Review of Financial Analysis*, vol. 76, no. 9, Article ID 101782, 2021.

[41] C. He, Z. Wen, K. Huang, and X. Ji, "Sudden shock and stock market network structure characteristics: a comparison of past crisis events," *Technological Forecasting and Social Change*, vol. 180, Article ID 121732, 2022.

[42] T. T. Cheng, J. L. Liu, W. Y. Yao, and A. B. Zhao, "The impact of COVID-19 pandemic on the volatility connectedness network of global stock market," *Pacific-Basin Finance Journal*, vol. 71, Article ID 101678, 2022.

[43] W. Jang, J. Lee, and W. Chang, "Currency crises and the evolution of foreign exchange market: evidence from minimum spanning tree," *Physica A: Statistical Mechanics and Its Applications*, vol. 390, no. 4, pp. 707–718, 2011.

[44] G. F. Zebende, "DCCA cross-correlation coefficient: quantifying level of cross-correlation," *Physica A: Statistical Mechanics and Its Applications*, vol. 390, no. 4, pp. 614–618, 2011.

[45] S. J. Devlin, R. Gnanadesikan, and J. R. Kettenring, "Robust estimation and outlier detection with correlation coefficients," *Biometrika*, vol. 62, no. 3, pp. 531–545, 1975.

[46] A. Kotsifakos, V. Athitsos, P. Papapetrou, J. Hollmén, and D. Gunopulos, "Model-based search in large time series databases," *ACM Transactions on Database Systems*, vol. 36, pp. 1–6, 2011.

[47] C. M. Hafner and O. Reznikova, "On the estimation of dynamic conditional correlation models," *Computational Statistics and Data Analysis*, vol. 56, no. 11, pp. 3533–3545, 2012.

[48] H. Mir, H. Al-Nashash, D. Kerr, A. All, and N. Thakor, "Spinal cord injury evaluation using morphological difference of somatosensory evoked potentials," in *Proceedings of the 5th*

International Conference on Bioinformatics and Biomedical Engineering, pp. 1–4, IEEE, Wuhan, China, May 2011.

[49] C. Myers, L. Rabiner, and A. Rosenberg, "Performance tradeoffs in dynamic time warping algorithms for isolated word recognition," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 28, no. 6, pp. 623–635, 1980.

[50] P. Senin, "Dynamic time warping algorithm review," *Information and Computer Science Department, University of Hawaii at Manoa Honolulu*, vol. 855, no. 1–23, p. 40, 2008.

[51] G. J. Wang, C. Xie, F. Han, and B. Sun, "Similarity measure and topology evolution of foreign exchange markets using dynamic time warping method: evidence from minimal spanning tree," *Physica A: Statistical Mechanics and Its Applications*, vol. 391, no. 16, pp. 4136–4146, 2012.

[52] M. Müller, *Information Retrieval for Music and Motion*, Springer, Berlin, Germany, 2007.

[53] Y. Y. Baydilli and I. Türker, "Is the world small enough? – a view from currencies," *International Journal of Modern Physics B*, vol. 33, no. 12, Article ID 1950120, 2019.

[54] M. Demirer, F. X. Diebold, L. Liu, and K. Yilmaz, "Estimating global bank network connectedness," *Journal of Applied Econometrics*, vol. 33, no. 1, pp. 1–15, 2018.

[55] Y. Mai, H. Chen, J. Z. Zou, and S. P. Li, "Currency comovement and network correlation structure of foreign exchange market," *Physica A: Statistical Mechanics and Its Applications*, vol. 492, pp. 65–74, 2018.

[56] G. J. Wang and C. Xie, "Tail dependence structure of the foreign exchange market: a network view," *Expert Systems with Applications*, vol. 46, pp. 164–179, 2016.

[57] G. J. Wang, C. Xie, Z. Q. Jiang, and H. Eugene Stanley, "Who are the net senders and recipients of volatility spillovers in China's financial markets?" *Finance Research Letters*, vol. 18, pp. 255–262, 2016.

[58] G. J. Wang, C. Xie, L. F. Zhao, and Z. Q. Jiang, "Volatility connectedness in the Chinese banking system: do state-owned commercial banks contribute more," *Journal of International Financial Markets, Institutions and Money*, vol. 57, pp. 205–230, 2018.

[59] G. J. Wang, C. Xie, K. He, and H. E. Stanley, "Extreme risk spillover network: application to financial institutions," *Quantitative Finance*, vol. 17, no. 9, pp. 1417–1433, 2017.

[60] X. F. Liu and C. K. Tse, "A complex network perspective of world stock markets: synchronization and volatility," *International Journal of Bifurcation and Chaos*, vol. 22, no. 6, Article ID 1250142, 2012.

[61] L. Liu and J. Wan, "A study of correlations between crude oil spot and futures markets: a rolling sample test," *Physica A: Statistical Mechanics and Its Applications*, vol. 390, no. 21-22, pp. 3754–3766, 2011.

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Research Article

Time-Frequency Connectedness between Shariah Indices in a Systemic Crisis Era

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We examine the time- and frequency-domain spillover connectedness between regional and world Shariah indices. The spillover index approach is employed with data over the period from April 30, 2012, to May 9, 2022, for African, American, Asian, European, and world emerging and developed markets' Shariah-based equity indices. The results indicate significant time- and frequency-dependent spillovers between Shariah indices. The world and developed markets' Shariah indices transmit the greatest return spillover to their African and Asian counterparts, which act as net recipients of system spillovers. Our findings show that Asian Shariah assets are a perfect hedge against all relevant market shocks over the last decade. Our findings have implications for Shariah market regulators, investors, practitioners, and policymakers.

1. Introduction

Complexities in financial markets result in heterogeneous market connectedness not only in conventional markets but also in faith-based investments. One of the notable faith-based investment vehicles is Shariah assets. Shariah indices contain equities that adhere to the Islamic Shariah rules established by Shariah scholars. As a corollary to the rigorous procedures followed in classifying equities as Shariah compliant, numerous stocks are screened out, resulting in a smaller Shariah index portfolio than the traditional benchmark [1, 2]. As a result, the issue of Shariah indices being underperformed by their conventional equivalents has been a concern for market participants [3]. This influences empirics, practitioners, and academics to validate this by analysing the performance of Shariah and conventional indexes over numerous years [1–16]. Given the credence that Shariah index portfolios may be outperformed by conventional portfolios, numerous prior scholarly assessments will be incomplete if the properties of Shariah markets (i.e., contributors to the Shariah index) towards risk reduction are unknown empirically.

Faith-based investments are gaining increasing interest among all classes of investors owing to the recent growth of the Islamic financial market and the ability of Shariah-compliant assets to meet investor needs [8, 14]. Central to portfolio management is the connectedness between assets [17–21], and the need to manage portfolios is highlighted by the devastating impacts of financial meltdowns over the last decade, notable amongst them being Brexit, the trade tension between China and the US, the COVID-19 pandemic, and the Russia-Ukraine conflict. Of the numerous empirical works on Shariah markets, little is known about the risk management characteristics of major Shariah indices across regions and the globe. The recent study by Balli et al. [7] has focused on firm-level data, which have little to offer in terms of Shariah index portfolios relative to regional Shariah indices.

Moreover, investors most likely adapt to changing market dynamics during crisis periods to reallocate assets and rebalance their portfolios based on their risk appetite [17, 22–26]. Theoretically, the fractal market hypothesis suggests that market response to shocks differs across time and trading horizons [27]. The implication is that the connectedness between markets would differ across short-, medium-, and long-term trading periods, yet existing works on Shariah markets fail to cater to this complexity in investor behaviour and market response.

Market participants mostly trade along investment horizons, and hence, such an analysis is key to determining how they allocate assets across both time and trading (frequency) horizons. Market participants and regulators alike need empirical evidence to influence their decisions on Shariah investments and market regulation, respectively. As a result, several questioning themes may be of concern to investors and policymakers. For instance, inter alia, to what extent are Shariah markets connected? Are there significant return spillovers between Shariah markets? Which markets are the largest transmitters or recipients? How are spillovers between Shariah markets distributed across trading horizons? Are Shariah markets susceptible to financial contagion? Are there diversification and safe-haven benefits between Shariah markets in the context of spillovers?

Answers to these questions warrant empirical assessments of the connectedness between Shariah markets. We contribute to the literature in this direction by investigating the return spillover connectedness between Shariah indices across the world. The studys' main contributions are as follows: First, novel to the literature, we provide rigorous assessments of the static (overall) and time- and frequency-varying connectedness of major Shariah indices. Such an analysis is instrumental to risk management and effective portfolio construction but is nonexistent in the empirical literature concerning Shariah portfolio indices. Second, through spillover analysis, we provide empirical evidence for risk management concerning investment in Shariah-based assets, and this is particularly beneficial to the growing investor base for Shariah-compliant assets in periods of heightened systemic crises such as the ongoing era of the coronavirus pandemic and the Russia-Ukrain geopolitical conflict. Spillover analysis is essential to reveal the directional linkages between diverse Shariah markets in a system and helps identify, on a pairwise basis, the contribution of each Shariah market to system spillovers and how they evolve across both time and frequency domains. These dynamics are important because the sample period captures the aforementioned key events, and as a result, knowing the evolution of connectedness between Shariah investments would influence the timely rebalancing of Shariah asset-dominated portfolios.

Third, the study period covers significant events, both past and present (such as Brexit, the financial meltdowns of Chinese and Russian markets, the US-China trade conflict, the COVID-19 pandemic, and the Russia-Ukraine war), in the history of financial markets over the last decade. These events provide a means of analysing the cross-market connectedness between Shariah assets over a wide range of financial crises, either of systemic or idiosyncratic character. This makes the use of time-frequency approaches relevant. Fourth, in addition to the world Shariah index, we cover Shariah portfolio indices from six major regions, viz., Africa, America, Asia, developed markets, emerging markets, and Europe. The use of these variables in a single study is new to the empirical literature.

Methodologically, to cater to heterogeneous market linkages and investor responses, we primarily employ the spillover index approach of Baruník and Křehlík [28]. This approach is based on heterogeneous shock frequency responses within a rolling window paradigm. It is effective in detailing the transmission sources of system spillovers, recipients of shocks, and the size of contagion (if any). More importantly, BK-18 isolates frequency-domain spillovers from aggregate spillovers through decomposition, which is necessary for detailing spillover dynamics across trading horizons for market participants. Given that market participants (policymakers) trade (plan) along heterogeneous investment horizons (short term, medium term, and long term), this approach is particularly important to this study, unlike the earlier approach of Diebold and Yilmaz [19], which assumes a static measure for spillovers.

The approach of Diebold and Yilmaz [19] has recently been modified by the authors of [29] in their time-varying parameter vector autoregression (TVP-VAR)-based spillover technique, but it does not segregate aggregate spillovers into their frequency components, as performed by the BK-18 approach. Therefore, to overcome the issue of arbitrary rolling window size and loss of observations through the rolling window process, as Antonakakis et al. [29] advocated, we supplement all our BK-18 estimates with the TVP-VAR-based spillover technique. No existing study employs these techniques while utilising return series from regional Shariah markets.

We find significant and more stable return spillovers between Shariah markets over the last decade. Our findings show that these spillovers are transitory as they dominate the short-term trading horizon. Shariah indices' connectedness is resistant to Brexit, the Chinese and Russian financial markets' meltdowns, and the US-China trade conflict but not to the systemic shocks of the COVID-19 pandemic. We found that Shariah portfolio indices from Asia, Africa, and emerging markets are diversifiers for Shariah indices from America, Europe, and developed markets during normal market conditions and safe havens during crisis periods.

In Section 2, we describe the methodology and provide a preliminary assessment of the data in Section 3. The main results are discussed in Section 4, and the conclusion is given in Section 5.

2. Methods

The [28] spillover index is employed to examine the dynamic connectedness and spillovers between Shariah-compliant regional indices. This approach helps show the time and frequency dynamics of regional Shariah indices. The BK-18 spillover index approach (See [29] for detailed steps on the TVP-VAR connectedness measure) is detailed as follows.

Generalised forecast error variance decompositions (GFEVDs) were utilised by Baruník and Křehlík [28] to measure connectedness, as championed by Diebold and Yilmaz [19]. Data are decomposed using the matrix of a vector autoregressive (VAR) model whose local covariance is stationary. From a K-variate procedure, $Y_t = (y_{1,t}, \ldots, y_{K,t})^{'}$ such that $t = 1, \ldots, T$ and $VAR(p)$ are given as

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t, \tag{1}$$

where coefficient matrices and white noise with (prospective nondiagonal) the covariance matrix Π are denoted as ϕ_i and ϵ_i, respectively. Each variable in system (1) and its p lags are regressed, as well as the p lags of all other variables. Consequently, ϕ holds inclusive information on the connections between all variables. Note that it is suitable to work with a $(K \times K)$ matrix $(\mathbf{I}_K - \varnothing_1 L - \ldots - \varnothing_p L^p)$ whose identity should be $\mathbf{I}_K$. A moving average $MA(\infty)$ bounds the VAR system when the representative equation $|\theta(z)|$ has its roots lying outside of the unit circle as

$$Y_t = \psi(L)\epsilon_t, \tag{2}$$

where $\psi(L)$ depicts an infinitive-lagged polynomial. The contribution of the kth variable (i.e., GFEVD) towards the element j's forecast error variance can be expressed as

$$\left(\Theta_H\right)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left(\left(\psi_h \Pi\right)_{j,k}\right)^2}{\sum_{h=0}^{H}\left(\psi_h \Pi \psi_{h^{'}}\right)_{j,j}}, \tag{3}$$

where $h = 1, \ldots, H$ and $\sigma_{kk} = (\Pi_{kk})$. Contributions by rows do not aggregate to 1, so owing to completeness, a standardised matrix Θ_H is generated as

$$\left(\widetilde{\Theta}_H\right)_{j,k} = \frac{\left(\Theta_H\right)_{j,k}}{\sum_{k=1}^{N}\left(\Theta_H\right)_{j,k}}. \tag{4}$$

Paired connectedness equation (4) may be summed for the system's overall connectedness. According to Diebold and Yilmaz [19], it is the share of variation in predictions brought about by errors other than own error such that

$$C_H = 100 * \frac{\sum_{j \neq k}\left(\widetilde{\Theta}_H\right)_{j,k}}{\sum \widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\left\{\widetilde{\Theta}_H\right\}}{\sum \widetilde{\Theta}_H}\right), \tag{5}$$

where $Tr\{.\}$ signifies the tracing operator and the denominator is the summation of the matrix's entire elements. Accordingly, relative to the other variables in the system, connectedness symbolises the contribution of the forecast variance. Then, bidirectional comovement may be assessed ("TO" and "FROM" variable i from all other variables k). NET connectedness is then measured as the difference between spillovers "TO" and "FROM."" Hence, a variable with a positive NET is a net propagator, whereas one with a negative NET acts as a net recipient of shocks.

Given a frequency response function $\psi(e)^{-i\omega} = \sum_h e^{-i\omega h}\psi_h$ whose coefficients are transformable by Fourier transformations ψ_h with $i = \sqrt{-1}$, Y_t, which is a spectral density, at frequency ω, $MA(\infty)$ can be defined as a filtered series.

$$S_{y(\omega)} = \sum_{h=-\infty}^{\infty} E\left(Y_t Y_{t-h}^{'}\right)e^{-i\omega h} = \psi\left(e^{-i\omega}\right)\Pi\psi^{'}\left(e^{+i\omega}\right), \tag{6}$$

where $S_{y(\omega)}$ represents the power spectrum detailing the variance's (Y_t) distribution for frequency constituents ω. A causal spectrum for $\omega \in (-\pi, \pi)$ is explained by equation (7) which reflects ith variable' s proportion resulting from the kth variable's shocks at a named frequency ω. Therefore, *within-frequency* causation based on the denominator is defined as

$$\left(\mathscr{F}(\omega)\right)_{j,k} = \frac{\sigma_{kk}^{-1}\left|\psi\left(e^{-i\omega}\right)\Pi_{j,k}\right|^2}{\left(\psi\left(e^{-i\omega}\right)\Pi\psi^{'}\left(e^{+i\omega}\right)\right)_{j,j}}. \tag{7}$$

We weigh $\left(\mathscr{F}(\omega)\right)_{j,k}$ by the frequency share of the variance of the jth variable to naturally decompose GFEVD into frequencies defined by the weighting function as

$$\Gamma_j = \frac{\left(\psi\left(e^{-i\omega}\right)\Pi\psi^{'}\left(e^{+i\omega}\right)\right)_{j,j}}{(1/2\pi)\int_{-\pi}^{\pi}\left(\psi\left(e^{-i\lambda}\right)\Pi\psi^{'}\left(e^{+i\lambda}\right)\right)_{j,j} d\lambda}, \tag{8}$$

aggregating to real-valued (Baruník and Křehlík [28] indicated that a squared modulus of the weighted complex numbers, which result in a real-valued quantity, is the generalised causation spectrum) figures up to 2π and is representative of the jth variable's index at a named frequency. Measuring connectedness across periods is practical for financial applications by market participants. Therefore, instead of quantifying the single-frequency connectedness, it is practical to perform quantification across frequency bands. Taking a formal depiction of the frequency band, d is defined as $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$, where GFEVDs are defined as

$$\left(\Theta_d\right)_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)\left(\mathscr{F}(\omega)\right)_{j,k} d\omega. \tag{9}$$

We can construct scaled (the scaling factor is 100, and from a practical application of the BK-18 connectedness approach, H serves as the least forecast horizon) generalised variance decomposition at the same frequency band d in the expression as

$$\left(\widetilde{\Theta}_d\right)_{j,k} = \frac{\left(\Theta_d\right)_{j,k}}{\sum_k\left(\Theta_d\right)_{j,k}}, \tag{10}$$

Hence, *within frequency* and frequency connectedness across d are, respectively, expressed as

$$C_d^W = 100.\left(1 - \frac{Tr\left\{\widetilde{\Theta}_d\right\}}{\sum \widetilde{\Theta}_d}\right), \tag{11}$$

$$C_d^F = 100.\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty} - \frac{Tr\left\{\widetilde{\Theta}_d\right\}}{\sum \widetilde{\Theta}_\infty}\right) = C_d^W.\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty}\right). \tag{12}$$

Note that C_d^W denotes the connectedness within a frequency band, and at a given frequency band, its weighting factor is derived from the power of the series. Conversely, C_d^F segregates the overall connectedness into discrete proportions that aggregate the overall connectedness index [28].

The frequency bands we utilised can be denoted as "$(\pi + 0.00001, \pi/4, \pi/8, \pi/32, \pi/64, 0)$" and follow the specifications in the extant literature [18, 30, 31]. Frequency bands $d_1\,(3.14 \sim 0.79)$, $d_2\,(0.79 \sim 0.39)$, $d_3\,(0.39 \sim 0.10)$, $d_4\,(0.10 \sim 0.05)$, and $d_5\,(0.05 \sim 0.00)$ correspond to daily bands of "1~4 (intraweek), 4~8 (intraweek-to-week), 8~32 (fortnight-to-month), 32~64 (month-to-quarter), and 64~∞ (quarter-and-beyond)."

A 100-day forecast horizon (H) and rolling window periods are specified. The set window sums up to a little beyond a quarter of annum, which is ample to deal with time variations. Under a timely risk management plan, within 100 trading days, investors have ample time to reassess the contribution of assets in their portfolios. Hence, a rolling window of 100 days, which sums up to a quarter, is specified in line with prior works [18, 32]. It must be noted that, although one's risk management preferences may influence the use of alternative forecast and rolling window size, the time-varying setting of the connectedness index yields qualitatively similar results, as shown by existing studies [33–35]. Under a rolling window system, the problem of exogenously specifying the beginning and ending dates of crises is eliminated [29]. Additionally, the application of spillover bands allows us to identify which spillover band dominates the overall spillovers between the variables of interest [36, 37].

3. Data and Preliminary Analysis

We employ the daily Shariah-compliant indices from Dow Jones (the DJIM Asia Pacific Developed TopCap Index, DJIM Developed Markets Index, DJIM Europe Index, DJIM World Emerging Markets Index, and DJIM World Index) and Standard & Poor's (S&P Africa Frontier Shariah and S&P Global 1200 Shariah) listings. The dataset spanned between April 30, 2012, and May 9, 2022, and all data were gleaned from https://www.spglobal.com/.

A trajectory of the raw and return series is presented in Figure 1. The raw series largely depicts similar trends, with S&P Africa Frontier Shariah being exceptional, owing to the relatively low market capitalisation. All other series depict a falling trend during the early days (to months) of 2020 and 2022, which respectively reflect the impact of COVID-19 and the Russia-Ukraine disturbances of the sampled regional Shariah markets. The volatility clusters spotted in the return series plots confirm the stylised facts vis-à-vis asset returns.

We report the descriptive summary of the returns on the studied stock markets in Table 1. The results confirm skewed and kurtosis distributions. Thus, the resultant skewness and kurtosis statistics depict a nonnormal distribution of all series and a leptokurtic distribution of Shariah markets.

These observations offer a strong motivation to employ the BK-18 technique, relative to the DY-12 static approach or just the TVP-VAR-based method, both of which do not express the overall connectedness across the frequency domain, to examine the dynamic connection between emerging and developed market stocks. Over the studied period, all regional Shariah indices indicate positive mean returns, but negative skewness suggests that negative returns were mostly recorded. This is unsurprising because the last decade has been full of uncertainties and unprecedented market downturns, causing irregularities in financial markets [9, 23].

4. Empirical Results

We report and discuss the main findings of the study in this section. Within the time-frequency space, we present intriguing findings on the overall spillover connectedness of regional Shariah markets. To ensure robust findings from onset, we report on the static connectedness between the studied markets to show the veracity of the findings from the primary approach used, the BK-18 spillover index. Since the DY-12 approach was improved by the authors of [29] in their time-varying parameter vector autoregression (TVP-VAR) connectedness measure, the static connectedness between markets is rather reported preliminarily to the time-frequency analysis from the BK-18 approach. The relevance of the static analysis is to show the supposed spillovers between Shariah indices altogether, but the approach only deals with the time space, implying that limited (or no) information will be available to investors that trade along trading horizons of short-, medium-, and long-term periods, which are only reflective in the frequency space, and hence, the BK-18 time-frequency approach is of significance.

4.1. Static Analysis. The overall connectedness measure of spillovers between regional Shariah markets is reported in Table 2. The overall degree of interconnectedness in the system is expressed by the total connectedness index (TCI), which is 66.79%, in the right bottom corner of Table 2. This means that the combined dynamics of the system variables may explain roughly 67% of the variations in system variables. We turn to the last but the third row "TO" to learn more about each variable's contribution to the system's interconnectivity. DJIM_World (102.01%), DJIM_Developed (98.2%), and S&P1200_Shariah (98.04%%) are the largest providers of spillover TO in the system. DJIM_Asia and S&P_Africa_Shariah transmit the least return spillovers. The last column "FROM" depicts the spillover received by each variable from the system. Again, we can see that DJIM_World, DJIM_Developed, and S&P1200_Shariah receive the largest system spillovers, while DJIM_Emerging and S&P_Africa_Shariah receive the least spillovers.

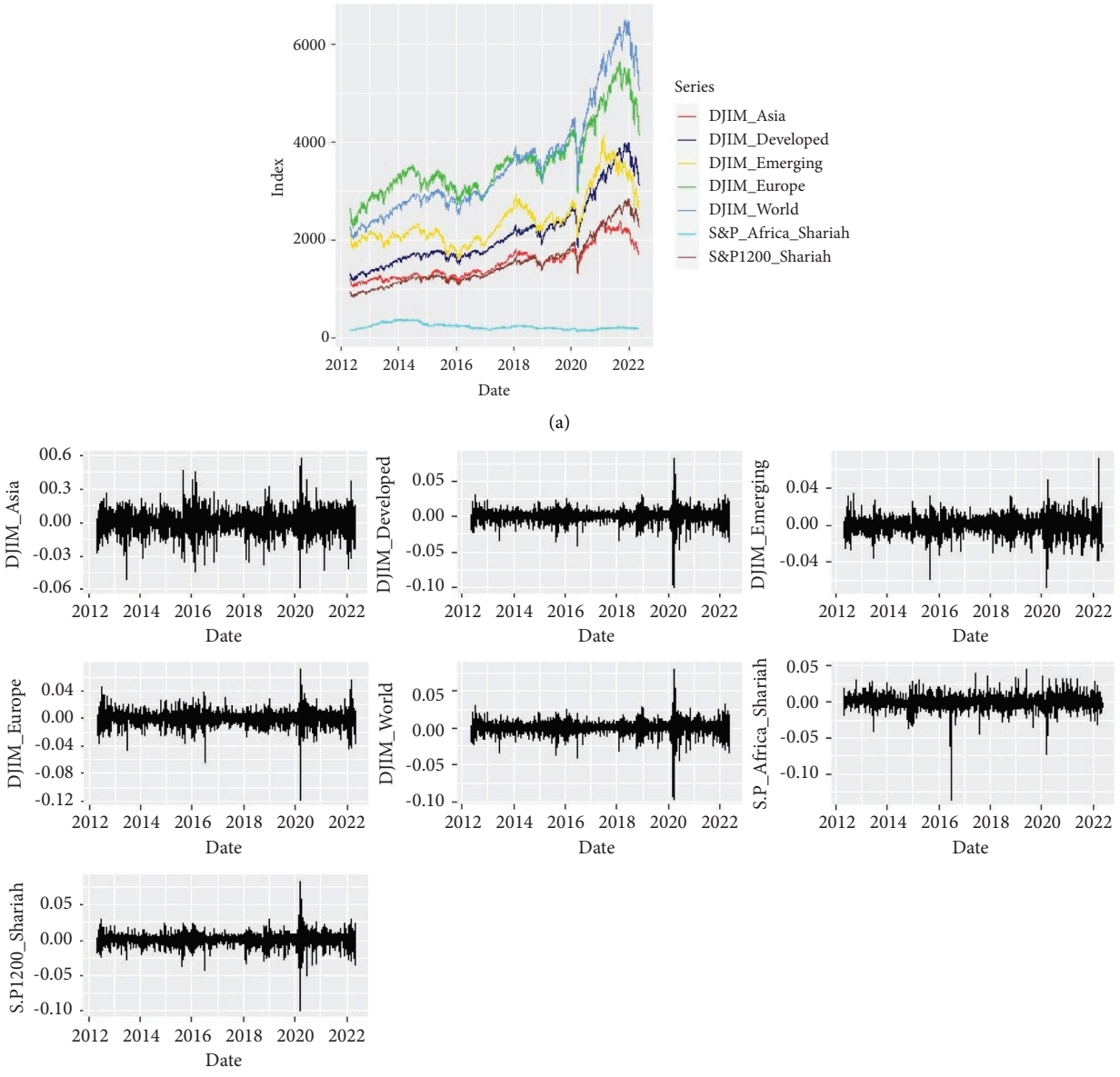

Figure 1: Time series plots of Shariah indices. (a) Raw series and (b) return series for seven regional Shariah indices.

Interestingly, findings from the static connectedness between regional Shariah markets reveal less idiosyncratic spillovers. Relative to conventional assets and other popularly known assets, which possess high idiosyncratic spillovers [18, 38], Shariah markets exhibit low self-induced spillovers. Except for S&P_Africa_Shariah, all other markets' idiosyncratic spillovers are generally below a third of the overall system spillovers they receive. This indeed distinguishes Shariah assets as a separate asset class whose return may be hardly replicated using simple combinations of traditional nonfaith-based assets.

Whereas the directional ("TO" and "FROM") analysis emphasises each variable's contribution to the system, net spillover transmitters and receivers must also be distinguished. The net spillover for each variable is shown in the penultimate row ("NET") of Table 2. A positive (negative) value indicates a net transmitter (receiver) of spillovers. Note that DJIM_Asia (−30.22%), S&P_Africa_Shariah (19.52%), DJIM_Emerging (17.06%), and DJIM_Europe (−1.04%) are net spillover recipients, whereas DJIM_World (24.80%), DJIM_Developed (21.66%), and S&P1200_Shariah (21.38%) are net spillover transmitters.

We turn to the pairwise spillover connectedness between regional Shariah markets. We use network analysis to properly evaluate the static pairwise connectedness of net transmitters and receivers of spillovers in the system. It is worth noting that this network plot shows the pairwise transmission of shocks between the system variables under the spillover connectedness model. This version of network connectivity has been employed in related works due to its

Table 1: Descriptive statistics.

	DJIM_Asia	DJIM_Developed	DJIM_Emerging	DJIM_Europe	DJIM_World	S&P_Africa_Shariah	S&P1200_Shariah
Panel A: sample statistics							
Observations	2599	2599	2599	2599	2599	2599	2599
Min	−0.0583	−0.0997	−0.0673	−0.1178	−0.0964	−0.1349	−0.0999
Max	0.0579	0.0825	0.0725	0.0705	0.0792	0.0443	0.0830
Average	0.0001	0.0003	0.0001	0.0002	0.0003	0.0000	0.0003
Std. dev	0.0096	0.0092	0.0095	0.0102	0.0089	0.0093	0.0092
Skewness	−0.2595	−0.9560	−0.4401	−0.7833	−0.9935	−1.4009	−0.9208
Kurtosis	3.1801	16.3810	5.3872	10.1810	16.1881	19.7960	16.3581
Normtest.W	0.9650***	0.8759***	0.9504***	0.9312***	0.8796***	0.9181***	0.8764***
Panel B: correlation matrix							
DJIM_Asia	1.0000						
DJIM_Developed	0.3629***	1.0000					
DJIM_Emerging	0.5682***	0.5836***	1.0000				
DJIM_Europe	0.3953***	0.7118***	0.6002***	1.0000			
DJIM_World	0.3980***	0.9964***	0.6497***	0.7283***	1.0000		
S&P_Africa_Shariah	0.3435***	0.9933***	0.5913***	0.6999***	0.9910***	1.0000	
S&P1200_Shariah	0.0971***	0.0921***	0.0988***	0.1191***	0.0958***	0.0873***	1.0000

Notes: this table presents the summary (panel A) and correlation (panel B) statistics for the studied Shariah indices. *** signifies a 1% significance level.

Table 2: Static connectedness of regional Shariah markets.

	DJIM_Asia	DJIM_Developed	DJIM_Emerging	DJIM_Europe	DJIM_World	S&P_Africa_Shariah	S&P1200_Shariah	FROM
DJIM_Asia	27.73	15.66	10.29	13.65	16.01	1.22	15.44	72.27
DJIM_Developed	6.85	23.46	8.20	13.74	23.22	1.37	23.16	76.54
DJIM_Emerging	11.13	12.81	34.50	11.25	15.71	1.01	13.59	65.50
DJIM_Europe	7.34	18.20	8.90	27.86	18.39	1.43	17.89	72.14
DJIM_World	7.28	22.60	9.87	13.67	22.79	1.32	22.47	77.21
S&P_Africa_Shariah	2.65	5.81	2.36	5.27	5.60	72.82	5.48	27.18
S&P1200_Shariah	6.81	23.13	8.81	13.52	23.07	1.31	23.35	76.65
TO	42.06	98.20	48.44	71.10	102.01	7.66	98.04	467.50
Inc. own	69.78	121.66	82.94	98.96	124.80	80.48	121.38	**TCI**
NET	−30.22	21.66	−17.06	−1.04	24.80	−19.52	21.38	**66.79**
NPDC	4.00	2.00	5.00	3.00	0.00	6.00	1.00	

Notes: "FROM" (last column) represents the system's return spillovers contributed by all other variables to a stated variable. "TO"" (fourth to the last row) displays return spillovers from a named variable to the system of all other variables. "NET" (penultimate row) shows the net directional return spillovers of each variable, while the net pairwise position is depicted by NPDC (last row). TCI (bold at the bottom of the last column) is the total connectedness index of the system of all variables. The TCI is an index measured in percentage. There is no significance level associated with the estimate.

ability to give a comprehensive view of static spillovers between the examined system of variables (see, e.g., [33, 34, 39, 40]). To ascertain the robustness of the findings from the BK-18 approach, we employ a 200-day rolling window analysis under the TVP-VAR connectedness model. This is in line with several studies that employ a 200-day window to analyse the time-varying connectedness between the variables [25, 34, 35, 41]. Our network analysis aids in identifying the net transmitters and net receivers of spillovers on a pairwise basis. Figure 2 shows the net pairwise connectivity patterns and linkages between the studied Shariah markets. The arrow's source denotes the spillover transmitter, while the arrow's edge denotes the spillover receiver for that particular pair.

On a pairwise level, we find that DJIM_World and DJIM_Developed emerge as the most influential Shariah markets, as they transmit the greatest spillovers in the system. The net positions of DJIM_Asia and S&P_Africa_Shariah are also shown by the network analysis.

Note that, in the static system, time-conditional effects that are buried in the aggregate show a noteworthy transient transmission of shocks [33, 42], and hence, relying on the complete period may obscure some patterns because of probable structural changes or varying trends in their linkages [9, 33]. Therefore, the connectivity component of a dynamic estimation utilising a rolling window technique may change. This leads us to our analysis of the system's dynamic connectedness under the BK-18 framework.

4.2. Time- and Frequency-Domain Analysis. By accounting for the evolution of total connection through time, the time-frequency spectrum analysis aids in determining the existence or absence of contagion. We proceed with our analysis by looking at the cross-frequency spillover effects across regional Shariah markets. This breakdown takes into consideration market players' changing expectations and requirements throughout time. There are five frequency bands ("intraweek, week-fortnight, fortnight-month, month-quarter, and quarter and beyond") for short- (Band 1), medium- (Bands 2 and 3), and long-term (Bands 4 and 5) spillovers, respectively, as shown in Table 3.

4.2.1. Overall Spillover Connectedness. From the overall spillover indices for all the studied Shariah markets (see Table 3), we find that the magnitude of spillovers reduces with increasing frequencies. Thus, in the short-term horizon (intraweek scale), spillovers are higher than in the medium- (monthly scale) and long-term (quarterly scale) horizons. For instance, the return spillover within the first band, 3.14~0.79, which approximates 1~4 days, is 44.17%, which reduces to 9.05%, 7.65%, 1.53%, and 0.77%, respectively through the second to fifth (0.79~0.00) spillover/frequency bands. Our findings are consistent with those of [18, 38], who used a similar methodology and found that short-term spillovers are more significant than intermediate-term spillovers for individual Islamic and conventional markets and between Islamic and BRICS markets, respectively.

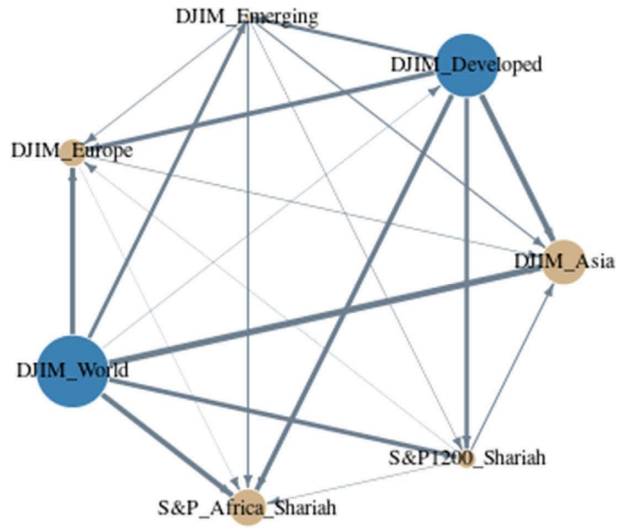

Figure 2: Static pairwise connectedness between regional Shariah markets. Notes: with a one-way direction arrow, arrows represent the net directional connectivity between two variables in the system. Blue (brown) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents the weighted average net total directional connectedness.

It is worth noting that individual Shariah markets are less influenced by their own shocks. This means that internal shocks are less significant to take much into consideration in asset allocation decisions between Shariah assets. Unlike the individual Islamic or conventional stock indices which may exhibit high idiosyncratic risks [9, 39, 43], assets that strictly comply with the Shariah standards, as monitored by S&P and Dow Jones, produce less idiosyncratic risks. A significant proportion of spillovers they endure emanate from external markets.

In Table 3, we reveal the net transmitters and recipients of spillovers among Shariah markets. The results suggest that, in the short term (3.14~0.79), the net transmitters (recipients) of spillovers among the regional Shariah markets are DJIM_World, DJIM_Developed, and S&P_Shariah (DJIM_Asia, DJIM_Emerging, S&P_Africa_Shariah, and DJIM_Europe). In the mid-to-long-term periods, similar observations are found in terms of the recipient/transmitter position of each Shariah market but in diminishing magnitudes.

To substantiate our findings, we present the time-frequency subtleties of the return spillovers among the regional Shariah markets in Figure 3.

Assessments of the dynamic connectedness help ascertain the extent to which the connectedness between Shariah markets evolves across different market periods and calendar years. When the analysis is conducted in the frequency domain, we can ascertain the extent to which the connectedness between Shariah markets differs in the short-, medium-, and long-term trading horizons. Impliedly, the frequency-domain spillover connectedness accumulates to the overall (static) spillover index. These features are combined with the BK-18 approach.

Table 3: Frequency-domain connectedness.

	DJIM_Asia	DJIM_Developed	DJIM_Emerging	DJIM_Europe	DJIM_World	S.P_Africa_Shariah	S.P1200_Shariah	FROM_ABS	FROM_WTH
The spillover table for the band: 3.14 to 0.79 (roughly corresponds to 1 to 4 days)									
DJIM_Asia	23.39	9.29	7.08	7.10	9.53	0.24	9.29	6.08	8.56
DJIM_Developed	3.48	18.42	7.04	10.21	18.31	0.40	18.20	**8.24**	**11.60**
DJIM_Emerging	5.99	8.78	22.13	7.74	10.36	0.26	9.05	6.03	8.49
DJIM_Europe	3.16	12.14	7.70	22.45	12.46	0.39	11.86	6.81	9.60
DJIM_World	3.73	17.53	8.12	10.06	17.65	0.39	17.38	8.17	11.51
S.P_Africa_Shariah	0.40	0.88	0.46	0.75	0.88	65.08	0.86	0.61	0.85
S.P1200_Shariah	3.27	18.34	7.32	10.05	18.29	0.40	18.61	**8.24**	**11.60**
TO_ABS	2.86	9.57	5.39	6.56	9.98	0.30	9.52	**44.17**	
TO_WTH	4.03	13.48	7.59	9.24	14.05	0.42	13.41		62.22
NET	−3.21	1.33	−0.64	−0.26	1.80	−0.31	1.28		
The spillover table for the band: 0.79 to 0.39 (roughly corresponds to 4 to 8 days)									
DJIM_Asia	4.04	2.71	2.01	1.94	2.82	0.02	2.65	**1.74**	**12.55**
DJIM_Developed	0.60	2.80	1.04	1.55	2.78	0.01	2.76	1.25	9.02
DJIM_Emerging	1.35	2.71	4.73	2.15	3.09	0.02	2.77	1.73	12.48
DJIM_Europe	0.73	2.83	1.38	3.72	2.85	0.02	2.78	1.51	10.94
DJIM_World	0.66	2.84	1.28	1.62	2.85	0.01	2.81	1.32	9.52
S.P_Africa_Shariah	0.18	0.41	0.19	0.32	0.41	12.55	0.40	0.27	1.98
S.P1200_Shariah	0.57	2.75	1.08	1.50	2.74	0.01	2.77	1.24	8.94
TO_ABS	0.58	2.04	1.00	1.30	2.10	0.01	2.02	**9.05**	
TO_WTH	4.22	14.73	7.22	9.38	15.18	0.09	14.64		65.44
NET	−1.15	0.79	−0.73	−0.22	0.78	−0.26	0.79		
The spillover table for the band: 0.39 to 0.10 (roughly corresponds to 8 to 32 days)									
DJIM_Asia	3.40	2.32	1.71	1.64	2.41	0.00	2.26	1.48	12.66
DJIM_Developed	0.50	2.32	0.86	1.28	2.30	0.00	2.29	1.03	8.85
DJIM_Emerging	1.16	2.36	4.03	1.86	2.68	0.00	2.40	**1.49**	**12.81**
DJIM_Europe	0.61	2.38	1.15	3.08	2.40	0.01	2.33	1.27	10.86
DJIM_World	0.55	2.37	1.06	1.35	2.38	0.00	2.34	1.10	9.40
S.P_Africa_Shariah	0.16	0.38	0.18	0.30	0.38	10.68	0.37	0.25	2.16
S.P1200_Shariah	0.47	2.28	0.89	1.25	2.27	0.00	2.30	1.02	8.77
TO_ABS	0.49	1.73	0.83	1.10	1.78	0.00	1.71	**7.65**	
TO_WTH	4.23	14.79	7.15	9.40	15.22	0.03	14.69		65.51
NET	−0.98	0.69	−0.66	−0.17	0.68	−0.25	0.69		
The spillover table for the band: 0.10 to 0.05 (Roughly corresponds to 32 days to 64 days)									
DJIM_Asia	0.68	0.47	0.34	0.33	0.48	0.00	0.45	0.30	12.68
DJIM_Developed	0.10	0.46	0.17	0.26	0.46	0.00	0.46	0.21	8.81
DJIM_Emerging	0.23	0.48	0.81	0.37	0.54	0.00	0.49	0.30	12.88
DJIM_Europe	0.12	0.48	0.23	0.62	0.48	0.00	0.47	**0.25**	**10.84**
DJIM_World	0.11	0.47	0.21	0.27	0.48	0.00	0.47	0.22	9.37
S.P_Africa_Shariah	0.03	0.08	0.04	0.06	0.08	2.15	0.08	0.05	2.20
S.P1200_Shariah	0.09	0.46	0.18	0.25	0.45	0.00	0.46	0.20	8.74
TO_ABS	0.10	0.35	0.17	0.22	0.36	0.00	0.34	**1.53**	
TO_WTH	4.24	14.80	7.14	9.41	15.23	0.01	14.70		65.52

Table 3: Continued.

	DJIM_Asia	DJIM_Developed	DJIM_Emerging	DJIM_Europe	DJIM_World	S.P_Africa_Shariah	S.P1200_Shariah	FROM_ABS	FROM_WTH
NET	−0.20	0.14	−0.13	−0.03	0.14	−0.05	0.14		
The spillover table for the band: 0.05 to 0.00 (roughly corresponds to 64 to inf days)									
DJIM_Asia	0.34	0.23	0.17	0.17	0.24	0.00	0.23	**0.15**	**12.68**
DJIM_Developed	0.05	0.23	0.09	0.13	0.23	0.00	0.23	0.10	8.81
DJIM_Emerging	0.12	0.24	0.40	0.19	0.27	0.00	0.24	**0.15**	**12.88**
DJIM_Europe	0.06	0.24	0.11	0.31	0.24	0.00	0.23	0.13	10.84
DJIM_World	0.06	0.24	0.11	0.14	0.24	0.00	0.23	0.11	9.37
S.P_Africa_Shariah	0.02	0.04	0.02	0.03	0.04	1.07	0.04	0.03	2.21
S.P1200_Shariah	0.05	0.23	0.09	0.12	0.23	0.00	0.23	0.10	8.74
TO_ABS	0.05	0.17	0.08	0.11	0.18	0.00	0.17	**0.77**	
TO_WTH	4.24	14.80	7.14	9.41	15.23	0.01	14.70		65.52
NET	−0.10	0.07	−0.07	−0.02	0.07	−0.03	0.07		

Notes: this table presents the total connectedness index of the system of all variables across five frequency bands ("intraweek, week-fortnight, fortnight-month, month-quarter, and quarter and beyond") for short- (Band 1), medium- (Bands 2 and 3), and long-term (Bands 4 and 5) spillovers, respectively.

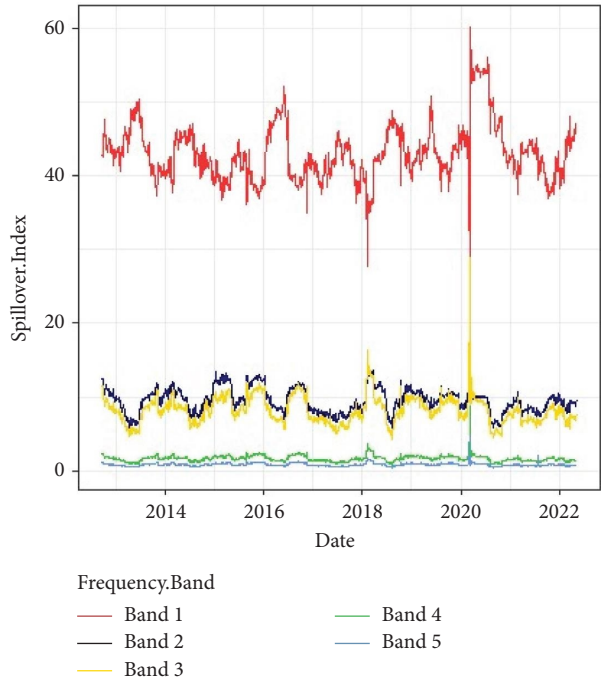

Figure 3: Dynamic return spillovers between regional Shariah markets. Notes: time- and frequency-domain return connectedness between Shariah regional markets is presented. Band 1 (red colour) represents short-term dynamics, Bands 2 (navy colour) and 3 (gold colour) depict the medium term, while the long-term dynamics are shown by Bands 4 (lime green) and 5 (cornflower blue). The horizontal axis displays the time domain, while the spillover indices (in %) are plotted against the vertical axis for the respective frequency bands.

The spillover connectedness between the sampled Shariah markets (see Figure 3) (note that our estimations provide qualitatively similar results under window sizes of 100, 200, and 400; for brevity, they are available upon request) ranges between 28% and 61% in the short term (Band 1), 5% and 28% in the intermediate term (Bands 2 and 3), and between 1% and 10% in the long term (Bands 4 and 5). The differences in spillover connectedness across time and frequency domains suggest that cross-market linkages for Shariah assets respond to changing market dynamics. It is not surprising that there were some moderate peaks in 2016, 2019, and 2020, particularly in the short term. These dates match significant events like the Brexit dialogues and vote in 2016, the trade tension between China and the US in 2019, and the emergence of the COVID-19 pandemic in 2020. This observation is expected since in stressed conditions, market participants usually rush into asset allocation and portfolio decisions in an attempt to secure the safety of portfolio returns amid worst-performing assets [17, 24, 26]. By doing so, safe assets like faith-based investments and non-traditional assets like bonds and commodities appeal to investors. Hence, the rush for these assets is most likely a cause for their high return linkages in the short term during tumultuous trading periods [44].

It must be noted that the most significant hikes among the identified periods were the ones in 2020 across all frequency bands (i.e., the short term, medium term, and long term). This period corroborates the coronavirus pandemic era. At the apogee of the pandemic, cross-asset and cross-market connectedness saw significant hikes [14, 45]. The intuition is that, amid the systemic risk accompanying the COVID-19 pandemic, the rush for safe assets augmented and caused market participants to move from one asset to another, causing high market connectivity among Shariah markets. It is expected that once Shariah assets are highly regulated as per the principles of Shariah, their returns are less likely to be affected by similar factors that affect the returns of conventional assets. Therefore, investors are most likely to be comfortable including such assets in their portfolios during crisis periods. The struggle for these faith-based assets in the early periods of the COVID-19 pandemic will cause their high connectedness in such a period as the competitive market hypothesis underscores [46]. The differences in the high connectivity across frequency bands during the same crises are attributable to the heterogeneity in market responses in such tumultuous periods, as the fractal market hypothesis explicates [27]. Thus, market participants adapt to market trends based on investment horizons, as represented by frequencies [8, 47, 48].

In the time-domain analysis, these findings are consistent with the dynamic spillovers under the TVP-VAR paradigm. This is shown by the TVP-VAR spillover connectedness in Figure 4.

In Figure 4, the dynamic spillovers, which are in the time domain only, under the TVP-VAR connectedness approach, depict comparable patterns with their time- and frequency-domain counterparts as shown by the BK-18 spillover connectedness approach. As indicated earlier, the significant hike in the system's connectivity relates to the COVID-19 era.

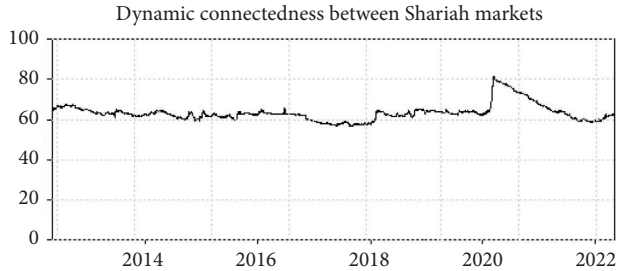

Figure 4: Dynamic spillovers between regional Shariah markets. Notes: time-varying spillover connectedness between regional Shariah markets is presented.

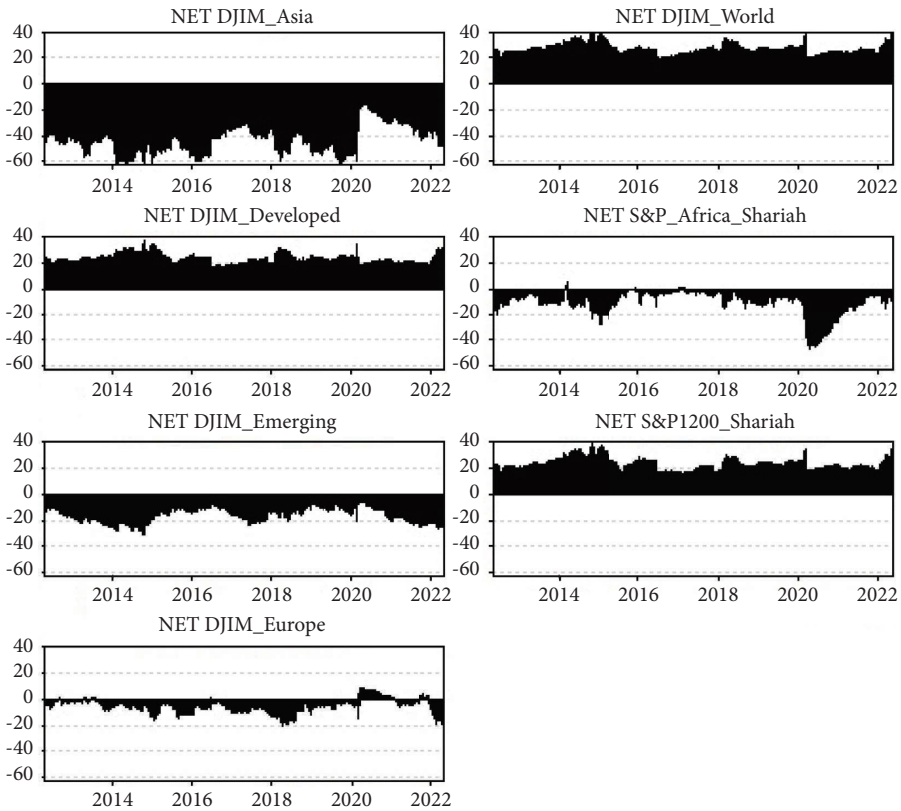

Figure 5: Directional and net spillovers between regional Shariah markets. Notes: the dynamic directional ("TO" and "FROM") and net pairwise spillover dynamics between regional Shariah markets is presented.

4.2.2. Directional Spillover Connectedness. So far, our general dynamic analysis has revealed that the interconnectedness of the variables in the system fluctuates throughout time. Analysing the contribution of each variable to the system's overall interconnectivity, on the other hand, is just as significant. This will aid in our understanding of each Shariah market's potential role in risk reduction. As a result, we explore each variable's dynamic return connectivity with the whole system. Figure 5 shows a pictorial elaboration on how each variable interacts with the system.

The net contribution of each variable to all other variables in the system of commodity classes is depicted in Figure 5. Positive (negative) values indicate that the variable is a net transmitter (recipient) in the system. The results are consistent with the main findings of the static and frequency-domain analysis. DJIM_Asia, DJIM_Emerging, and S&P_Africa_Shariah are all consistent net recipients across the study period. The net position of DJIM_Europe proved inconsistent, particularly in the systemic risk era of the COVID-19 pandemic. DJIM_World, DJIM_Developed, and S&P1200_Shariah are all transmitters of system spillovers. We infer, based on these results, that the risk-reduction role of Shariah indices is mostly preserved for DJIM_Asia, DJIM_Emerging, and S&P_Africa_Shariah but is dynamic for DJIM_Europe, which switches between a net transmitter and a net recipient across systemic crisis periods.

Significant observations from the dynamic analysis suggest that DJIM_Asia, DJIM_Emerging, and

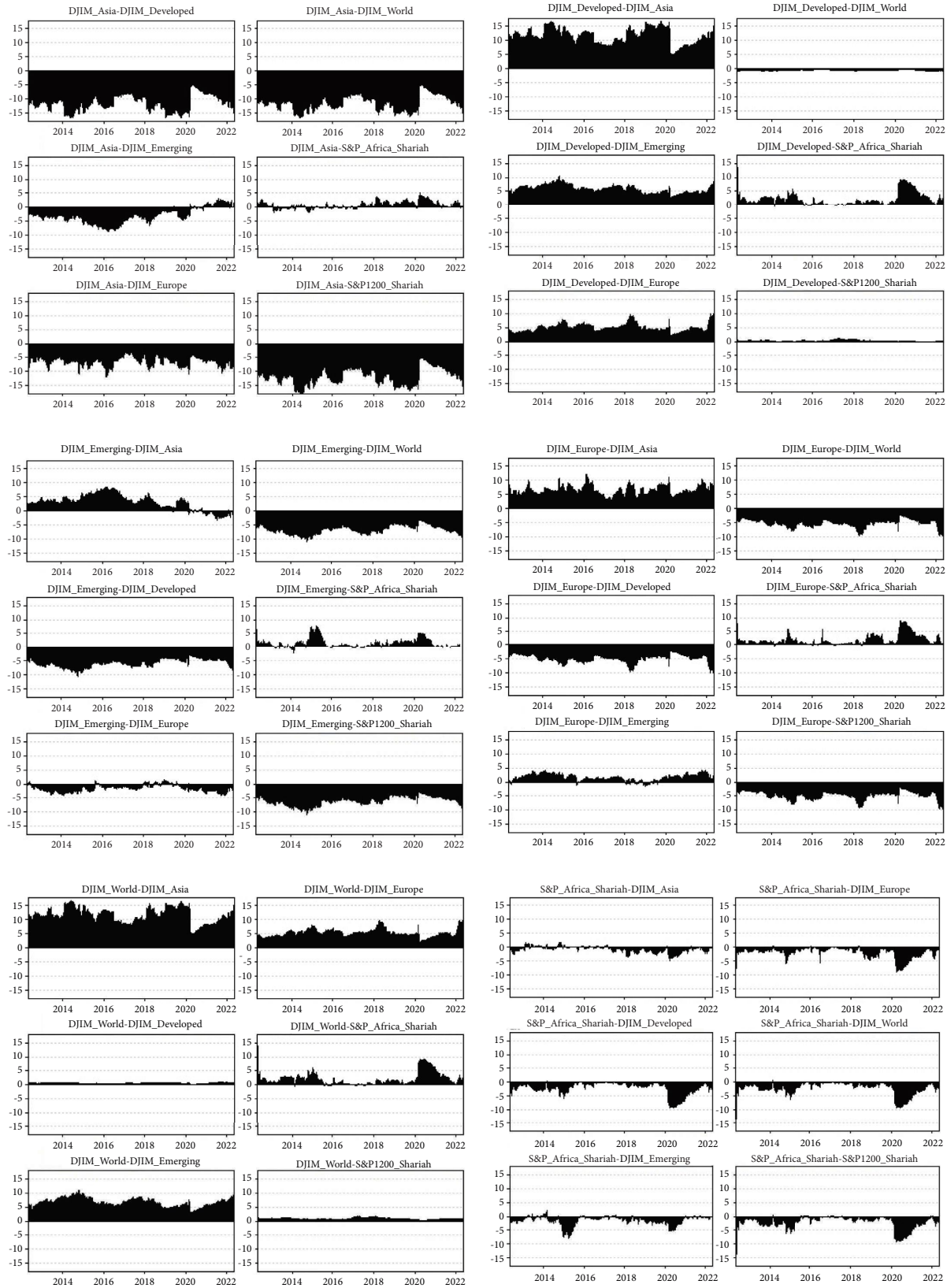

Figure 6: Continued.

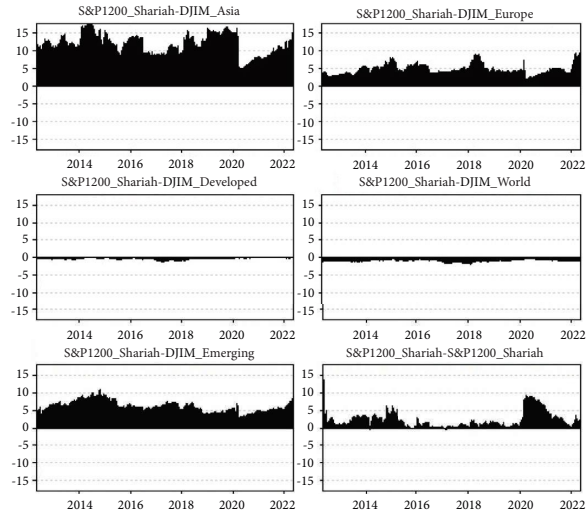

Figure 6: Dynamic pairwise spillovers between regional Shariah markets. Notes: dynamic net pairwise spillovers between regional Shariah markets are presented.

S&P_Africa_Shariah could retain their diversification benefits across time and stand the chance of being consistent safe havens for the other Shariah markets whose returns are detrimentally affected in turbulent trading periods. Notable strategic combinations between pairs (the pairwise spillover dynamics between Shariah markets are reported in Figure 6) of Shariah markets could be achieved by investors who seek to combine faith-based assets.

Furthermore, the hikes in the system's connectedness during the COVID-19 systemic crisis signify that the fundamental linkages between Shariah markets could be affected in turbulent trading periods despite the credence that they may withstand shocks. This observation is consistent with existing studies that find increased connectedness between financial assets during crisis periods [25, 34, 35, 41]. This observation corroborates the contagion literature by Forbes and Rigobon [49, 50], which suggested that there is contagion when the connectedness between markets undergoes a significant change after one market or country has experienced a shock. Given the significant increases in the connectedness between the studied Shariah markets, we document that regional Shariah markets are susceptible to contagious spillovers during systemic risk periods. Our findings are backed by recent works that underscore contagion [18, 51–54], arousing market susceptibilities to implied volatilities (Alsubaie et al., 2022) [55]. The sources of these contagious spillovers are the Shariah markets of developed markets and the world market.

Having found dynamic connectedness between regional Shariah markets, we advocate that investors adapt to evolving market dynamics, in line with the adaptive market hypothesis, by rebalancing their portfolios when new markets emerge as a result of structural breaks [22], as expounded by the fractal market hypothesis [27]. However, in adapting to new markets created from structural changes, investors should consider the dynamic behaviour of individual Shariah markets after incorporating their appetite for risks and rewards [8, 47, 48].

5. Conclusions and Recommendations

We examined the dynamic spillover connectedness between seven regional Shariah-based equity markets (i.e., DJIM Asia Pacific Developed TopCap Index, DJIM Developed Markets Index, DJIM Europe Index, DJIM World Emerging Markets Index, DJIM World Index, S&P Africa Frontier Shariah, and S&P Global 1200 Shariah). The dataset covered the period from April 30, 2012, to May 9, 2022. Spillover index techniques were employed to ascertain the extent to which Shariah markets move across time and frequency domains, which markets are the largest transmitters or recipients, whether Shariah markets are susceptible to financial contagion, and whether there are diversification and safe-haven benefits between Shariah markets.

Our findings suggest significant time- and frequency-varying spillovers between regional Shariah markets. Across the time domain, we underscore a significant hike in connectivity in the systemic crisis occasioned by the COVID-19 pandemic. Consistent with the existing literature, we conclude that connectedness between assets was driven by the systemic risk associated with the COVID-19 pandemic. At the apogee of the pandemic, cross-asset and cross-market connectedness saw a significant rise [14, 45, 55]. Across the frequency domain, we report that spillovers are largely short-lived and that Shariah markets are less susceptible to idiosyncratic shocks. These observations are consistent with the work by Bossman and Owusu Junior et al. [9], who found that spillovers between Islamic markets are dominant in the short term. Shariah markets are susceptible to financial contagion emanating from systemic crises, and the propagators of contagion are the Shariah indices of American, European, developed, and world markets. Given their net

recipient positions, African, Asian, and emerging market Shariah indices are more susceptible to contagious spillovers during systemic crises. Furthermore, our findings suggest significant diversification potential between regional Shariah investments. Indicatively, Shariah equity returns from Asian, African, and emerging markets are consistent diversifiers for their counterpart from European, developed, and world Shariah markets.

Findings from the time-varying analysis indicate that the hikes in connectedness between regional Shariah indices over the last decade are negligible, except for the COVID-19 pandemic era. This could be attributed to the novelty of the systemic crisis occasioned by the COVID-19 pandemic relative to those propagated by Brexit or the US-China trade conflict. Impliedly, market regulation should incorporate systemic risk factors that drive the connectedness between Shariah markets to peaked levels. Strategic asset allocation between Shariah assets should take into consideration the time- and frequency-domain dynamics and take advantage of the diversification potential between regional Shariah markets. We note that, from the position of net spillovers, some regional markets are net transmitters, while others are net recipients of spillovers. Hence, for investors and portfolio managers, the relevance of cross-regional and cross-asset investments is highlighted. Investors and portfolio managers can focus on the net position of various regional Shariah markets to ascertain a well-diversified portfolio and hedge downside risks during contagious periods like pandemics and geopolitical conflicts.

Future studies could consider the extent to which specific international shocks affect the returns on Shariah markets. To cater to asymmetries and nonlinearities, future studies could employ quantile-based methods to examine the conditional dependencies between global shocks and Shariah-based asset returns from individual countries rather than regional markets. This could ascertain the plausible differences between constituent Shariah markets from various regions. The overall market integration between Shariah assets could also be examined using wavelet techniques. It would also be fascinating to see future studies analysing the sensitivity of markets towards extreme spillovers during crisis periods. Ascertaining the system connectedness in network analysis for various frequencies could also be undertaken in future studies.

Data Availability

All data are available at https://www.spglobal.com/.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] N. Al Rahahleh and M. I. Bhatti, "Empirical comparison of Shariah-compliant vs. conventional mutual fund performance," *International Journal of Emerging Markets*, 2022.

[2] S. M. Alsubaie, K. H. Mahmoud, A. Bossman, and E. Asafo-Adjei, "Vulnerability of sustainable Islamic stock returns to implied market volatilities: an asymmetric approach," *Discrete Dynamics in Nature and Society*, 2022.

[3] M. B. H. Aarif, M. R. I. Rafiq, and A. N. M. Wahid, "Do 'Shariah' indices surpass conventional indices? A study on Dhaka Stock Exchange," *International Journal of Islamic and Middle Eastern Finance and Management*, vol. 14, no. 1, pp. 94–113, 2021.

[4] D. Ashraf, "Performance evaluation of Islamic mutual funds relative to conventional funds: empirical evidence from Saudi Arabia," *International Journal of Islamic and Middle Eastern Finance and Management*, vol. 6, no. 2, pp. 105–121, 2013.

[5] T. Aziz, J. Marwat, A. Zeeshan, Y. Paracha, and L. Al-haddad, "Do Islamic stock markets diversify the financial uncertainty risk ? Evidence from selected Islamic countries," *Journal of Asian Finance, Economics and Business*, vol. 8, no. 3, pp. 31–38, 2021.

[6] S. Bahloul, M. Mroua, and N. Naifar, "Are Islamic indexes, Bitcoin and gold, still "safe-haven" assets during the COVID-19 pandemic crisis?" *International Journal of Islamic and Middle Eastern Finance and Management*, vol. 15, 2021.

[7] F. Balli, M. Billah, H. O. Balli, and A. De Bruin, "Spillovers between sukuks and shariah-compliant equity markets," *Pacific-Basin Finance Journal*, vol. 72, Article ID 101725, 2022.

[8] A. Bossman, "Information flow from COVID-19 pandemic to Islamic and conventional equities: an ICEEMDAN-induced transfer entropy analysis," *Complexity*, vol. 2021, Article ID 4917051, 20 pages, 2021.

[9] P. Owusu Junior, A. M. Adam, E. Asafo-Adjei, E. Boateng, Z. Hamidu, and E. Awotwe, "Time-frequency domain analysis of investor fear and expectations in stock markets of BRIC economies," *Heliyon*, vol. 7, no. 10, Article ID e08211, 2021.

[10] M. Ghaemi Asl and M. M. Rashidi, "Dynamic diversification benefits of Sukuk and conventional bonds for the financial performance of MENA region companies: empirical evidence from COVID-19 pandemic period," *Journal of Islamic Accounting and Business Research*, vol. 12, no. 7, pp. 979–999, 2021.

[11] S. J. H. Shahzad, R. Ferrer, L. Ballester, and Z. Umar, "Risk transmission between Islamic and conventional stock markets: a return and volatility spillover analysis," *International Review of Financial Analysis*, vol. 52, pp. 9–26, 2017.

[12] Z. Umar, "Islamic vs. conventional equities in a strategic asset allocation framework," *Pacific-Basin Finance Journal*, vol. 42, pp. 1–10, 2017.

[13] Z. Umar, S. J. H. Shahzad, R. Ferrer, and F. Jareño, "Does Shariah compliance make interest rate sensitivity of Islamic equities lower? An industry level analysis under different market states," *Applied Economics*, vol. 50, no. 42, pp. 4500–4521, 2018.

[14] Z. Umar and M. Gubareva, "Faith-based investments and the COVID-19 pandemic: analyzing equity volatility and media coverage time-frequency relations," *Pacific-Basin Finance Journal*, vol. 67, Article ID 101571, 2021.

[15] Z. Umar and T. Suleman, "Asymmetric return and volatility transmission in conventional and Islamic equities," *Risks*, vol. 5, no. 2, p. 22, 2017.

[16] L. Yarovaya, A. H. Elsayed, and S. Hammoudeh, "Determinants of spillovers between Islamic and conventional financial markets: exploring the safe haven assets during the COVID-19 pandemic," *Finance Research Letters*, vol. 43, Article ID 101979, 2021.

[17] E. Asafo-Adjei, A. M. Adam, and P. Darkwa, "Can crude oil price returns drive stock returns of oil producing countries in Africa ? Evidence from bivariate and multiple wavelet," *Macroeconomics and Finance in Emerging Market Economies*, vol. 1–19, pp. 1–19, 2021.

[18] A. Bossman, Z. Umar, S. K. Agyei, and P. Owusu Junior, "A new ICEEMDAN-based transfer entropy quantifying information flow between real estate and policy uncertainty," *Research in Economics*, 2022.

[19] F. X. Diebold and K. Yilmaz, "Better to give than to receive: Predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, vol. 28, no. 1, pp. 57–66, 2012.

[20] S. Nasreen, S. A. A. Naqvi, A. K. Tiwari, S. Hammoudeh, and S. A. R. Shah, "A wavelet-based analysis of the co-movement between Sukuk bonds and shariah stock indices in the GCC region: Implications for risk diversification," *Journal of Risk and Financial Management*, vol. 13, no. 4, p. 63, 2020.

[21] M. T. Suleman, R. McIver, and S. H. Kang, "Asymmetric volatility connectedness between Islamic stock and commodity markets," *Global Finance Journal*, vol. 49, no. June, Article ID 100653, 2021.

[22] S. K. Agyei, A. M. Adam, A. Bossman et al., "Does volatility in cryptocurrencies drive the interconnectedness between the cryptocurrencies market? Insights from wavelets," *Cogent Economics & Finance*, vol. 10, no. 1, 2022.

[23] S. K. Agyei, P. Owusu Junior, A. Bossman, and E. Y. Arhin, "Situated information flow between food commodity and regional equity markets: an EEMD-based transfer entropy analysis," *Discrete Dynamics in Nature and Society*, vol. 2022, pp. 1–28, 2022.

[24] E. Asafo-Adjei, P. Owusu Junior, and A. M. Adam, "Information flow between global equities and cryptocurrencies: a vmd-based entropy evaluating shocks from covid-19 pandemic," *Complexity*, vol. 2021, Article ID 4753753, 25 pages, 2021.

[25] Z. Umar, A. Bossman, N. Iqbal, and X. V. Vo, "Dynamic connectedness and spillovers between yield curve's constituents and commodities," *SSRN Electronic Journal*, 2022.

[26] P. Owusu Junior, S. Frimpong, A. M. Adam et al., "COVID-19 as information transmitter to global equity markets: Evidence from CEEMDAN-based transfer entropy approach," *Mathematical Problems in Engineering*, vol. 2021, Article ID 8258778, 19 pages, 2021.

[27] E. E. Peters, *Fractal market analysis: applying chaos theory to investment and economics*, John Wiley & Sons, Hoboken, NJ, USA, 1994, https://books.google.com.gh/books?hl=en&lr=&id=_bkoySKyc_cC&oi=fnd&pg=PA27&dq=+E.E.+Peters&ots=sPxlouW6JK&sig=nI6OvrXXJ0alDf3z2pspMQujHJU&redir_esc=y#v=onepage&q&f=false.

[28] J. Baruník and T. Křehlík, "Measuring the frequency dynamics of financial connectedness and systemic risk," *Journal of Financial Econometrics*, vol. 16, no. 2, pp. 271–296, 2018.

[29] N. Antonakakis, I. Chatziantoniou, and D. Gabauer, "Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions," *Journal of Risk and Financial Management*, vol. 13, no. 4, p. 84, 2020.

[30] A. K. Tiwari, J. Cunado, R. Gupta, and M. E. Wohar, "Volatility spillovers across global asset classes: Evidence from time and frequency domains," *The Quarterly Review of Economics and Finance*, vol. 70, pp. 194–202, 2018.

[31] A. K. Tiwari, M. Shahbaz, H. M. Hasim, and M. M. Elheddad, "Analysing the spillover of inflation in selected Euro-area countries," *Journal of Quantitative Economics*, vol. 17, no. 3, pp. 551–577, 2019.

[32] P. Owusu Junior, I. Alagidede, and G. Tweneboah, "Shape-shift contagion in emerging markets equities: Evidence from frequency-andtime-domain analysis," *Economics and Business Letters*, vol. 9, no. 3, pp. 146–156, 2020.

[33] D. Y. Aharon, Z. Umar, and X. V. Vo, "Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies," *Financial Innovation*, vol. 7, no. 1, pp. 59–25, 2021.

[34] D. Y. Aharon, Z. Umar, M. I. A. Aziz, and X. v. Vo, "COVID-19 related media sentiment and the yield curve of G-7 economies," *The North American Journal of Economics and Finance*, vol. 61, no. March, Article ID 101678, 2022.

[35] Z. Umar, S. Aziz, and D. Tawil, "The impact of COVID-19 induced panic on the return and volatility of precious metals," *Journal of Behavioral and Experimental Finance*, vol. 31, Article ID 100525, 2021a.

[36] A. A. Shah and A. B. Dar, "Exploring diversification opportunities across commodities and financial markets: Evidence from time-frequency based spillovers," *Resources Policy*, vol. 74, no. September, Article ID 102317, 2021.

[37] Q. Sun, X. Gao, H. An, S. Guo, X. Liu, and Z. Wang, "Which time-frequency domain dominates spillover in the Chinese energy stock market?" *International Review of Financial Analysis*, vol. 73, Article ID 101641, 2021.

[38] W. Mensi, K. H. Al-Yahyaee, X. V. Vo, and S. H. Kang, "Modeling the frequency dynamics of spillovers and connectedness between crude oil and MENA stock markets with portfolio implications," *Economic Analysis and Policy*, vol. 71, pp. 397–419, 2021.

[39] W. Mensi, M. Shafiullah, X. V. Vo, and S. H. Kang, "Volatility spillovers between strategic commodity futures and stock markets and portfolio implications: Evidence from developed and emerging economies," *Resources Policy*, vol. 71, no. January, Article ID 102002, 2021.

[40] Z. Umar, I. Yousaf, and D. Y. Aharon, "The relationship between yield curve components and equity sectorial indices: Evidence from China," *Pacific Basin Finance Journal*, vol. 68, no. May, Article ID 101591, 2021.

[41] M. Akhtaruzzaman, S. Boubaker, and Z. Umar, "COVID–19 media coverage and ESG leader indices," *Finance Research Letters*, vol. 45, Article ID 102170, 2022.

[42] J. Kurka, "Do cryptocurrencies and traditional asset classes influence each other?" *Finance Research Letters*, vol. 31, pp. 38–46, 2019.

[43] R. Khalfaoui, M. Boutahar, and H. Boubaker, "Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis," *Energy Economics*, vol. 49, pp. 540–549, 2015.

[44] S. K. Agyei, P. Owusu Junior, A. Bossman, E. Asafo-Adjei, O. Asiamah, and A. M. Adam, "Spillovers and contagion between BRIC and G7 markets: New evidence from time-frequency analysis," *PLoS ONE*, vol. 17, no. 7, Article ID e0271088, 2022c.

[45] Z. Umar and M. Gubareva, "The relationship between the COVID-19 media coverage and the Environmental, Social and Governance leaders equity volatility: a time-frequency wavelet analysis," *Applied Economics*, vol. 53, no. 27, pp. 3193–3206, 2021b.

[46] P. Owusu Junior, A. M. Adam, E. Asafo-Adjei, E. Boateng, Z. Hamidu, and E. Awotwe, "Time-frequency domain analysis of investor fear and expectations in stock markets of BRIC economies," *Heliyon*, vol. 7, no. 10, Article ID e08211, 2021a.
[47] L. Kristoufek, "Fractal markets hypothesis and the global financial crisis: wavelet power evidence," *Scientific Reports*, vol. 3, no. 1, pp. 2857–7, 2013.
[48] A. S. Kumar and S. R. Padakandla, "Testing the safe-haven properties of gold and bitcoin in the backdrop of COVID-19: a wavelet quantile correlation approach," *Finance Research Letters*, vol. 47, Article ID 102707, 2022.
[49] K. J. Forbes and R. Rigobon, "Measuring contagion: conceptual and empirical issues," in *International Financial Contagion*Springer US, New York, NY, USA, 2001.
[50] K. J. Forbes and R. Rigobon, "No contagion, only interdependence: measuring stock market comovements," *The Journal of Finance*, vol. 57, no. 5, pp. 2223–2261, 2002.
[51] M. Akhtaruzzaman, S. Boubaker, and A. Sensoy, "Financial contagion during COVID–19 crisis," *Finance Research Letters*, vol. 38, Article ID 101604, 2021.
[52] Y. Guo, P. Li, and A. Li, "Tail risk contagion between international financial markets during COVID-19 pandemic," *International Review of Financial Analysis*, vol. 73, Article ID 101649, 2021.
[53] B. Hamdi, M. Aloui, F. Alqahtani, and A. Tiwari, "Relationship between the oil price volatility and sectoral stock markets in oil-exporting economies: evidence from wavelet nonlinear denoised based quantile and Granger-causality analysis," *Energy Economics*, vol. 80, pp. 536–552, 2019.
[54] W. Mohti, A. Dionísio, I. Vieira, and P. Ferreira, "Financial contagion analysis in Frontier markets: evidence from the US subprime and the Eurozone debt crises," *Physica A: Statistical Mechanics and its Applications*, vol. 525, pp. 1388–1398, 2019.
[55] G. K. Amoako, E. Asafo-Adjei, K. Mintah Oware, and A. M. Adam, "Do volatilities matter in the interconnectedness between world energy commodities and stock markets of BRICS?" *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 1030567, 13 pages, 2022.

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Research Article

Technological Change and Market Conditions: Evidence from Bitcoin Fork

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This article examines the impact of technological changes to cryptocurrency—known as "forking" that triggers blockchain splits—on market conditions. Despite the explicit distinction in log return distributions between the two splitting blockchains, adopting new technology does not result in a disparity in market conditions: no significant difference exists in market efficiency and long-term market equilibrium between the two splitting blockchains. Technological changes accompanying market separation do not impede the underlying uniformity in market conditions. The findings suggest that mutual information flows linked to market liquidity explain the results between the new and old forks.

1. Introduction

> "The 10,000 altcoins tried all manner laughable physics and computer science failed things."—Adam Back (on Twitter), *Forbes*, May 16, 2021.

The cryptocurrency market experiences technological changes in the form of forking, which is classified into two types: soft and hard. Both forks refer to changes to (i) a protocol of blockchain networks and (ii) data structures. A soft fork indicates a change that is backward compatible, whereas a hard fork denotes a change that is not backward compatible and results in two versions of the same blockchain. In particular, the fragile nature of consensus in blockchain technology (e.g., the debate over security issues) provides the opportunity for technological change, resulting in blockchain splits caused by a hard fork. The controversy about the benefits of and challenges to adopting new technology triggered the first hard fork—splitting Bitcoin. Although hard forks—particularly splitting Bitcoin—were implemented several times, this article concentrates on Bitcoin Cash, ranked within the top five in terms of market capitalization among all cryptocurrencies. This offshoot of Bitcoin, called Bitcoin Cash, referred to as the "old" fork, whereas the change-implemented Bitcoin is called the "new" fork. A hard fork, generated from the absence of a consensus or a divergence of beliefs, changes market sentiments and leads to diverging price movements. By creating multiple versions of the same blockchain, hard forks contribute to an increase in technological diversity. The old and new forks manifest large price fluctuations after the split: in the first five days, Bitcoin rose by approximately 19.7% and Bitcoin Cash declined by approximately 43.9%.

As a result, market fundamentals are examined and an underlying factor causing changes in market conditions is investigated further. In particular, we estimated the Hurst exponent (HE) to test the weak-form efficient market hypothesis (EMH) [1] and calculated the entropy to capture uncertainty and the degree of long-run market equilibrium. Despite significant differences in descriptive statistics and

probability density functions, technological divergence does not result in a disparity in market conditions in terms of market efficiency and long-term market equilibrium. The factor driving the main results is explained by mutual information flows linked to market liquidity via transfer entropy.

Since the seminal work of Fama [2], prior studies on market conditions—particularly in economics literature—have focused on market efficiency. However, recent studies on the Bitcoin market provided mixed evidence: some studies reported evidence of inefficiency [3–10], whereas others demonstrated that the market is efficient [11, 12], or at the very least, moves toward efficiency with the launch of Bitcoin futures and liquidity expansion [13–16]. Moreover, although many studies have been conducted on Bitcoin market's efficiency, studies on the impact of forking on the cryptocurrency market, particularly with its efficiency, have been extremely limited.

Another strand of literature on Bitcoin's market conditions studies the uncertainty and randomness of price series by employing the concept of long-term equilibrium in the economic context. In this article, the long-run equilibrium refers to the statistical equilibrium of the balance of each system [17–19]. The findings mostly suggested that the Bitcoin market was rife with randomness, unpredictability, and disorder [20, 21]. However, prior studies on long-run equilibrium are still limited for the cryptocurrency market in comparison to other financial markets, such as stock [22, 23], energy [19, 24, 25], and real estate [17, 26, 27]. In particular, to the best of our knowledge, no single study has been conducted to assess the long-run equilibrium in the new and old fork markets by using the concept of entropy.

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the results and discussion. Finally, Section 4 provides the conclusion.

2. Data and Methodology

2.1. Data. The daily prices of two splitting blockchains, such as Bitcoin and Bitcoin Cash, are retrieved immediately following the hard fork: the first hard fork splitting Bitcoin occurred on August 1, 2017. All data are in US dollars and are obtained from CoinMarketCap, which provides trading data, including the exchange activities of 2,543 cryptocurrencies in 20,295 markets. Our dataset spans the period from splitting the two blockchains to June 5, 2019, with 674 observations. For further analysis, both price series are stationarized, converting the price series into log returns. Table 1 summarizes the descriptive statistics.

Over the sample period, the log returns of Bitcoin Cash vary more significantly than those of Bitcoin, implying greater market uncertainty. The return series of old and new forks are distributed with nonnegative skewness and positive excess kurtosis. Unlike Bitcoin, which has a skewness close to zero, Bitcoin Cash has positive skewness, indicating an asymmetric distribution. Therefore, investors favor a positive skew and love risk in the old fork market, complying with the classical expected utility theory [28] and indicating a smaller downside risk [29]. The old fork also showed larger excess kurtosis than the new fork, which denotes a fatter tail, resulting in a more leptokurtic distribution.

Table 1: Descriptive statistics of daily log returns.

	Mean	Min.	Max.	Std.	Skewness	Kurtosis
Bitcoin	0.00	−0.21	0.23	0.04	0.01	6.34***
Bitcoin Cash	0.00	−0.45	0.43	0.09	0.65***	9.29***

Note: *** denotes significance at the 1% level.

2.2. Hurst Exponent. The HE was used to test the weak-form EMH. Following Hurst [30, 31] and Mandelbrot and Wallis [32, 33], we defined the R/S statistic as follows:

$$(R/S)_n = c \times n^{HE}, \tag{1}$$

where n is the length of the subseries, c is a constant, and $(R/S)_n$ is the mean value of the rescaled range for all subseries of length n. The R/S statistics and the estimated standard deviation S_n are given by the following:

$$\begin{aligned}(R/S)_n &= \frac{1}{S_n}\left[\max_{1\le t\le n}\sum_{k=1}^{t}\left(r_k-\overline{r}_n\right)-\min_{1\le t\le n}\sum_{k=1}^{t}\left(r_k-\overline{r}_n\right)\right],\\ S_n &= \sqrt{\frac{1}{n}\sum_{k=1}^{t}\left(r_k-\overline{r}_n\right)^2},\end{aligned} \tag{2}$$

where t is the number of successive subintervals, r_k denotes the return at time k, and $\overline{r}_n$ indicates the mean value of the return series.

To confirm the robustness of the results, we estimate the corrected HE [34] and the classical HE. Specifically, by estimating the slope of $(R/S - AL)_n$ versus n in a log-log plot, we defined the corrected HE as follows:

$$(R/S - AL)_n = (R/S)_n - E(R/S)_n + \sqrt{\frac{n\pi}{2}}, \tag{3}$$

where $E(R/S)_n$ is approximated by the following:

$$E(R/S)_n = \begin{cases} \dfrac{(n-0.5)\Gamma\left((n-1)/2\right)}{\sqrt[n]{\pi}\,\Gamma(n/2)}\displaystyle\sum_{i=1}^{n-1}\sqrt{(n-i)/i}, & (\text{for } n\le 340),\\ \dfrac{(n-0.5)}{\sqrt[n]{n\pi/2}}\displaystyle\sum_{i=1}^{n-1}\sqrt{(n-i)/i}, & (\text{for } n>340),\end{cases} \tag{4}$$

where Γ denotes the Euler gamma function.

2.3. Entropy. Entropy is used to measure the long-run market equilibrium and to capture uncertainty with a small information loss [22, 35, 36]. In particular, entropy measures the dispersion of probability allocation to each state rather than that of realized outcomes; therefore, it is robust to extremes other than volatility [37]. Following Shannon [38],

we define entropy (H) for the discrete random variable X as follows:

$$H(X) = -\sum_{i=1}^{M} p(x_i)\ln\ p(x_i), \tag{5}$$

where $p(x_i)$ and M are the probability mass function and the number of states, respectively.

This study uses two key approaches to calculate the Shannon entropy to ensure the robustness: (i) Shannon entropy through histogram, which has long been demonstrated to be a rigorous density estimator [39], is relatively simple to draw. However, the feasibility could be more dependent on the sample size and thus limited in use [22] and (ii) Shannon entropy via symbolic time series analysis (STSA), which has been extensively applied in various fields of study (i.e., physics, information theory, and finance), has been verified to be robust to noise [22, 35] and competitive in capturing uncertainty, particularly with time series data in finance [25]. Meanwhile, STSA may necessitate a better command of demanding calculations. First, the histogram-based entropy of the discrete random variable X is obtained by the following equation:

$$H(X) = -\sum_{i=1}^{N} \widehat{f}(x_i)\ln \widehat{f}(x_i), \tag{6}$$

where N refers to the number of intervals and $\widehat{f}(x_i)$ denotes a histogram estimate of the underlying probability mass function when X equals x_i [40].

Second, the dispersion of probability allocation onto the dynamic rise–fall pattern of consecutive price series was detected using STSA [22, 41]. The symbolization of consecutive return series is conducted as 1s for the positive returns and 0s for the others [42]. Subsequently, we determined the size of the rolling window to quantify the subsequence bundles composed of S binary numbers. Each subsequence bundle is converted from a binary sequence to a new decimal number, that is, X^S [22]. Then, the entropy of the random variable X^S is derived as follows:

$$H\left(X^S\right) = -\sum_{i=1}^{M-(S-1)} p\left(x_i^S\right)\log_2\ p\left(x_i^S\right), \tag{7}$$

where M is the number of outcomes in the entire series. In the end, the normalized Shannon entropy is given by the following:

$$h\left(X^S\right) = \frac{1}{S}H\left(X^S\right). \tag{8}$$

Hereafter, the mention of "Shannon entropy" or simply "entropy" refers to a normalized one, that is, $h(X^S)$.

2.3.1. Transfer Entropy. Transfer entropy detecting the information flow between the two markets is calculated as a proxy for the cause–effect relationship. By considering the attributes of the interactions, transfer entropy quantifies the amount of information transport in a nonsymmetric manner. In particular, finding nonzero rates of information transmission in both directions implies a dynamic correlation in producing and receiving information between the two time series [43–45]. Following Schreiber [43], we define the transfer entropy from system Y to X as follows:

$$TE_{Y\longrightarrow X} = \sum p\left(x_{n+1}, x_n^{(k)}, y_n^{(l)}\right)\left(\log\ p\left(x_{n+1}|x_n^{(k)}, y_n^{(l)}\right) - \log\ p\left(x_{n+1}|x_n^{(k)}\right)\right), \tag{9}$$

where $x_n^{(k)} = (x_n, \cdots, x_{n-k+1})$ and $y_n^{(l)} = (y_n, \cdots, y_{n-l+1})$ are the processes given by the k and l dimensional delay vectors, respectively. Therefore, $TE_{Y\longrightarrow X}$ reveals that asymmetry—the degree of dependence of X on Y—discerns the driving and responding sources [43].

We also consider the effective transfer entropy (ETE) to correct the noise caused by the finite size of the data. The ETE is derived as follows [46]:

$$ETE_{Y\longrightarrow X} = TE_{Y\longrightarrow X}(k, l) - \frac{1}{M}\sum_{i=1}^{M} TE_{Y_{(i)}\longrightarrow X}(k, l), \tag{10}$$

where $Y_{(i)}$ indicates the randomly shuffled variable Y. Accordingly, ETE is calculated by subtracting the arithmetic mean of the randomized transfer entropy values from the estimated transfer entropy value [47].

3. Results and Discussion

The Kolmogorov–Smirnov (KS) and Jarque–Bera (JB) tests are conducted to examine the difference between the two distributions: the new and old forks. As indicated in Table 2, the null hypothesis of the KS test can be rejected for both splitting blockchains, implying the significant difference between the two log return distributions. Additionally, the JB test indicates that neither Bitcoin nor Bitcoin Cash is normally distributed. Figure 1 further confirms these results: the new and old forks exhibit clearly different distributions, and both are close to the Laplace rather than the Gaussian distribution, in particular, near the center and the tail part.

However, two splitting blockchains reveal similar market conditions in terms of market efficiency and long-term equilibrium. First, HE is estimated to test the weak-form EMH, which examines price fairness, for the new and old fork markets. As shown in Table 3, both markets have relatively high values of classical and corrected HE ($HE > 0.5$), indicating a long-range dependence with no significant difference between the two, such as clustering tendency and delayed response to information flows [48]. Such persistence reinforces the predictability of the market and provides evidence of market inefficiency [49, 50]. However, two price series might move with a different trend, and the market could fluctuate according to different volatility clustering. Therefore, the long-term market equilibrium could differ between the new and old fork markets, unlike similar market efficiency.

Second, the Shannon entropy is estimated through two approaches, including histogram- and STSA-based, to determine the distance from the long-term market equilibrium

Table 2: Comparison between the two samples: Bitcoin and Bitcoin Cash.

	KS statistic	JB statistic
Bitcoin	0.15^{***}	$3.07 \times 10^{2***}$
Bitcoin Cash		$1.10 \times 10^{3***}$

The Kolmogorov–Smirnov (KS) statistic reports the outcome of a nonparametric equality test, the null hypothesis of which is that two samples are drawn from the same distribution. Meanwhile, the Jarque–Bera (JB) statistic documents the results of a normality test based on a Monte Carlo simulation, whose null hypothesis is that both skewness and excess kurtosis are all zero: the sample follows the normal distribution. *** denotes significance at the 1% level.

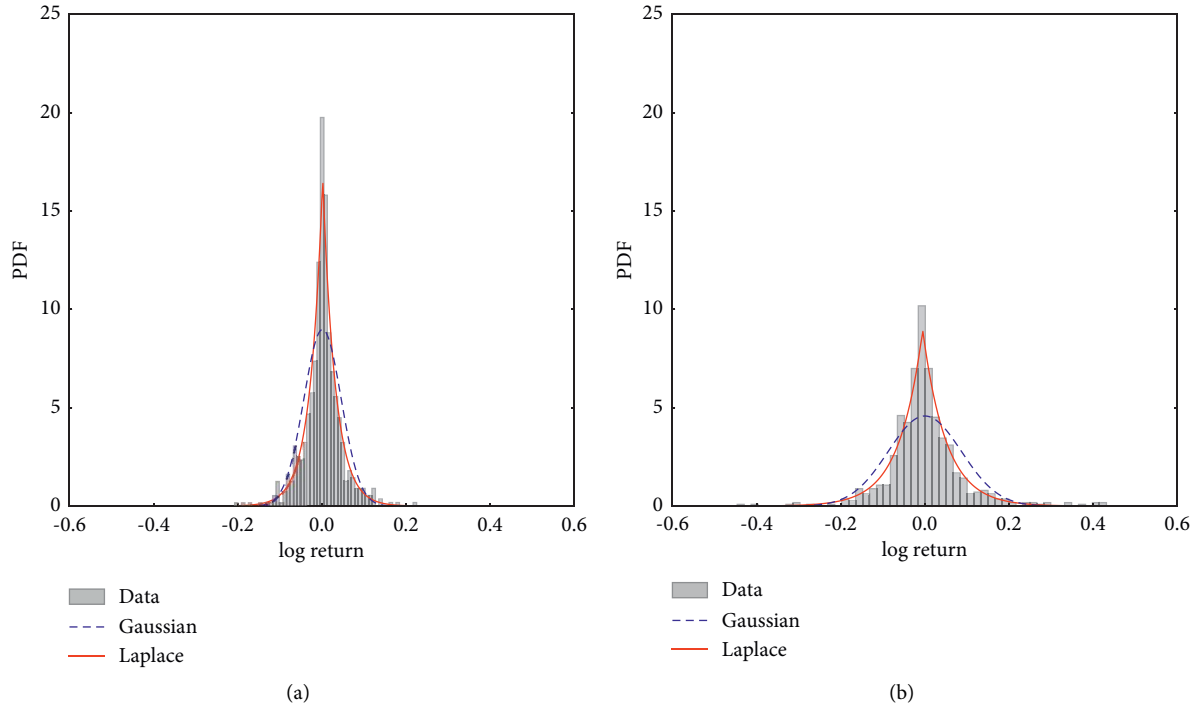

Figure 1: Probability density function of log returns in the new and old forks. Following the Freedman–Diaconis rule [39], we plotted the histograms of both datasets with the optimal bin width of 0.84×10^{-2} (Bitcoin) and 1.66×10^{-2} (Bitcoin Cash). There are two strands of rules for determining the optimal bin width: the Scott rule and the Freedman–Diaconis rule. The former is best suited for data that are close to being normally distributed, whereas the latter is less sensitive to outliers and thus better suited for data with heavy tails. As Figure 1 indicates, the data do not match well with the normal distribution; thus, the Freedman–Diaconis rule is used. (a) Bitcoin. (b) Bitcoin Cash.

Table 3: Hurst exponent.

	Classical	Corrected
Bitcoin	0.68 ± 0.00	0.54 ± 0.00
Bitcoin Cash	0.69 ± 0.01	0.55 ± 0.01

The estimated values of each measure with one standard error are presented. To validate the robustness, we estimated both the classical and corrected HE values with a minimum length of the subseries 2. The minimum subseries length (n) defines the length of the subseries when splitting a time series. This paper sets the minimum length of the subseries as $n = 2, \ldots, N/2$, where N indicates the length of the entire time series.

Table 4: Shannon entropy.

	Histogram	STSA
Bitcoin	0.75 ± 0.07	0.94 ± 0.02
Bitcoin Cash	0.76 ± 0.06	0.92 ± 0.03

The estimated values of each measure with one standard error are presented: the mean and standard deviation of entropy were calculated monthly basis (STSA: symbolic time series analysis).

on both new and old fork markets. As shown in Table 4, the Shannon entropy demonstrates the balance between the two markets, implying that the probability allocations onto (i) each state and (ii) dynamic rise–fall patterns are similar to high randomness in the two markets. This study considers the Shannon entropy as an optimal measure of long-run equilibrium, particularly in equilibrium systems [51] and determines whether each market is close to long-term market equilibrium. In summary, despite technological changes, the market conditions of the new and old forks are equivalent in terms of market efficiency and long-run market equilibrium. The term "long-term equilibrium" refers to statistical equilibrium, which is widely used in physics and information theory and is derived by maximizing the system's entropy, indicating the system's most likely state [18]. To enhance the robustness of the results on the market conditions, we further apply the power-law exponent (PLE), one of the most effective and powerful indicators for scaling behavior [52]. The results are summarized in the Appendix.

Table 5: Transfer entropy by quantile-based estimation.

Transfer entropy		Effective transfer entropy	
Bitcoin ⟶ Bitcoin Cash	0.03***	Bitcoin ⟶ Bitcoin Cash	0.02
Bitcoin Cash ⟶ Bitcoin	0.02**	Bitcoin Cash ⟶ Bitcoin	0.01

The directional link shown with the arrow represents the information flows between the new and old forks. For transfer entropy, ** and *** indicate significance at the 5% and 1% levels, respectively.

Table 6: Power-law exponent.

	Top 5%	Bottom 5%
Bitcoin	3.90 ± 0.98	3.25 ± 0.80
Bitcoin Cash	2.44 ± 0.61	2.53 ± 0.62

We estimate the power-law exponents (PLEs) based on the ordinary least square method in the positive and the negative tails of the normalized return distributions. Because the ranking process allows the residuals to be positively autocorrelated, the standard error (SE) could be incorrect. In this paper, the SE of the PLE is calculated from $\widehat{\xi}(n/2)^{-(1/2)}$, asymptotic SE of PLE $\widehat{\xi}$ [55].

The preceding results are explained using information flows related to market liquidity [53, 54]. In particular, transfer entropy distinguishes the bidirectional information flows between the new and old forks. As shown in Table 5, transfer entropy in both directions is statistically significant, implying that the new and old forks interact with each other. Accordingly, mutual information flows mitigate market uncertainty and alleviate investors' distrust. Moreover, the ETE supports the robustness of our findings: it is not due to random noise [46]. Therefore, significant mutual information flows linked to sufficient liquidity of Bitcoin Cash contribute to the two splits having similar market conditions. Since August 2017, Bitcoin Cash has been ranked in the top five cryptocurrencies in terms of market capitalization. Bitcoin splits other than Bitcoin Cash, such as Bitcoin Gold and Bitcoin Diamond, have far smaller market capitalizations. These are approximately 890–1,300 times smaller than Bitcoin in terms of market capitalization [54].

4. Conclusion

Using price series data, this study examines the market conditions for the two splitting blockchains, identifying commonalities and differences in the supporting technologies. The hard forks in cryptocurrency provide a novel setting for examining how technological advancements result in underlying market conditions that differ between the old and the new. The two splitting cryptocurrencies are clearly coupled in terms of market conditions, such as market efficiency and long-term equilibrium, despite the disparity in technology adoption. This study hypothesizes and finds supporting evidence that information flows linked to market liquidity can be attributed to similar market conditions of splitting blockchains.

As the cryptocurrency market is based on consensus-building systems, technological issues, such as hard forks, are likely to arise frequently. Our finding, significant bidirectional information flows between Bitcoin and Bitcoin Cash, suggests that the two cryptocurrencies could be used as hedging tools for one another. Moreover, monitoring information flows in conjunction with market liquidity could help policymakers and investors better understand and respond to future technological changes.

Appendix

As a signature for the collective phenomenon, PLE ($\widehat{\xi}$) for the tail of the normalized return distribution is estimated based on the ordinary least squares (OLS) method [55, 56]:

$$1 - F(x) = P(X > x) \sim x^{-\xi}, \tag{A.1}$$

where $F(x)$ denotes the cumulative density function. Taking the logarithm on both sides, we obtain the PLE as the slope of the estimated regression line from the following linear relationship [57, 58]:

$$\ln P(X > x) = c - \xi \ln x + \epsilon, \tag{A.2}$$

where c is a constant and ϵ is an identically and independently distributed error term following a normal distribution.

Table 6 summarizes the PLEs for Bitcoin and Bitcoin Cash. The authors choose the top and bottom 5% as critical values for estimating the PLEs of the positive and negative tails separately [59–61]. As shown in Table 6, the values of PLEs of Bitcoin and Bitcoin Cash exhibit the evidence of scaling behavior. All the PLEs summarized in Table 6 exhibit no significant difference between Bitcoin and Bitcoin Cash. In more detail, the two splitting blockchains follow the inverse cubic law, commonly found in the tails of stock returns [55, 60, 62], suggesting that both returns manifest a heavier tail as stocks do. These results further support the fact that market conditions between the two splitting blockchains are reached on par.

Data Availability

The daily prices of two splitting blockchains, such as Bitcoin and Bitcoin Cash, are retrieved immediately after the hard fork: the first hard fork splitting Bitcoin occurred on August 1, 2017. All data are in US dollars and are provided by CoinMarketCap, which provides trading data, including the exchange activities of 2,543 cyrptocurrencies in 20,295 markets.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] E. F. Fama, "The behavior of stock-market prices," *Journal of Business*, vol. 38, no. 1, pp. 34–105, 1965.

[2] E. F. Fama, "Efficient capital markets: a review of theory and empirical work," *The Journal of Finance*, vol. 25, no. 2, pp. 383–417, 1970.

[3] D. Aggarwal, "Do Bitcoins follow a random walk model?" *Research in Economics*, vol. 73, no. 1, pp. 15–22, 2019.

[4] M. E. Alaoui, E. Bouri, and D. Roubaud, "Bitcoin price–volume: a multifractal cross-correlation approach," *Finance Research Letters*, vol. 31, pp. 374–381, 2019.

[5] J. Alvarez-Ramirez, E. Rodriguez, and C. Ibarra-Valdez, "Long-range correlations and asymmetry in the Bitcoin market," *Physica A: Statistical Mechanics and Its Applications*, vol. 492, pp. 948–955, 2018.

[6] K. H. Al-Yahyaee, W. Mensi, H.-U. Ko, S.-M. Yoon, and S. H. Kang, "Why cryptocurrency markets are inefficient: the impact of liquidity and volatility," *The North American Journal of Economics and Finance*, vol. 52, Article ID 101168, 2020.

[7] P. Ferreira, L. Kristoufek, and E. J. d A. L. Pereira, "DCCA and DMCA correlations of cryptocurrency markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 545, Article ID 123803, 2020.

[8] L. Kristoufek and M. Vosvrda, "Cryptocurrencies market efficiency ranking: not so straightforward," *Physica A: Statistical Mechanics and Its Applications*, vol. 531, Article ID 120853, 2019.

[9] F. N. Zargar and D. Kumar, "Informational inefficiency of Bitcoin: a study based on high-frequency data," *Research in International Business and Finance*, vol. 47, pp. 344–353, 2019.

[10] W. Zhang, P. Wang, X. Li, and D. Shen, "The inefficiency of cryptocurrency and its cross-correlation with dow jones industrial average," *Physica A: Statistical Mechanics and Its Applications*, vol. 510, pp. 658–670, 2018.

[11] A. Brauneis and R. Mestel, "Price discovery of cryptocurrencies: Bitcoin and beyond," *Economics Letters*, vol. 165, pp. 58–61, 2018.

[12] W. C. Wei, "Liquidity and market efficiency in cryptocurrencies," *Economics Letters*, vol. 168, pp. 21–24, 2018.

[13] A. F. Bariviera, M. J. Basgall, W. Hasperué, and M. Naiouf, "Some stylized facts of the Bitcoin market," *Physica A: Statistical Mechanics and Its Applications*, vol. 484, pp. 82–90, 2017.

[14] G. Köchling, J. Müller, and P. N. Posch, "Does the introduction of futures improve the efficiency of Bitcoin?" *Finance Research Letters*, vol. 30, pp. 367–370, 2019.

[15] A. Sensoy, "The inefficiency of Bitcoin revisited: a high-frequency analysis with alternative currencies," *Finance Research Letters*, vol. 28, pp. 68–73, 2019.

[16] A. Urquhart, "The inefficiency of Bitcoin," *Economics Letters*, vol. 148, pp. 80–82, 2016.

[17] H. Jang, Y. Song, and K. Ahn, "Can government stabilize the housing market? The evidence from South Korea," *Physica A: Statistical Mechanics and Its Applications*, vol. 550, Article ID 124114, 2020.

[18] E. T. Jaynes, "Information theory and statistical mechanics," *Physics Reviews*, vol. 106, no. 4, pp. 620–630, 1957.

[19] K. Joo, J. H. Suh, D. Lee, and K. Ahn, "Impact of the global financial crisis on the crude oil market," *Energy Strategy Reviews*, vol. 30, Article ID 100516, 2020.

[20] S. Lahmiri, S. Bekiros, and A. Salvi, "Long-range memory, distributional variation and randomness of Bitcoin volatility," *Chaos, Solitons & Fractals*, vol. 107, pp. 43–48, 2018.

[21] D. Stosic, D. Stosic, T. B. Ludermir, and T. Stosic, "Exploring disorder and complexity in the cryptocurrency space," *Physica A: Statistical Mechanics and Its Applications*, vol. 525, pp. 548–556, 2019.

[22] K. Ahn, D. Lee, S. Sohn, and B. Yang, "Stock market uncertainty and economic fundamentals: an entropy-based approach," *Quantitative Finance*, vol. 19, no. 7, pp. 1151–1163, 2019.

[23] L. Kristoufek and M. Vosvrda, "Measuring capital market efficiency: long-term memory, fractal dimension and approximate entropy," *European Physical Journal B: Condensed Matter Physics*, vol. 87, no. 7, pp. 162–169, 2014.

[24] E. Martina, E. Rodriguez, R. Escarela-Perez, and J. Alvarez-Ramirez, "Multiscale entropy analysis of crude oil price dynamics," *Energy Economics*, vol. 33, no. 5, pp. 936–947, 2011.

[25] M. d C. Ruiz, A. Guillamón, and A. Gabaldón, "A new approach to measure volatility in energy markets," *Entropy*, vol. 14, no. 1, pp. 74–91, 2012.

[26] Y. Chen, Y. Cai, and C. Zheng, "Efficiency of Chinese real estate market based on complexity-entropy binary causal plane method," *Complexity*, vol. 2020, pp. 1–15, 2020.

[27] Ö Ömer, "Dynamics of the US housing market: a quantal response statistical equilibrium approach," *Entropy*, vol. 20, no. 11, p. 831, 2018.

[28] D. Bernoulli, "Exposition of a new theory on the measurement of risk," *Econometrica*, vol. 22, no. 1, pp. 23–36, 1954.

[29] C. Menezes, C. Geiss, and J. Tressler, "Increasing downside risk," *The American Economic Review*, vol. 70, no. 5, pp. 921–932, 1980.

[30] H. E. Hurst, "Long-term storage capacity of reservoirs," *Transactions of the American Society of Civil Engineers*, vol. 116, no. 1, pp. 770–799, 1951.

[31] H. E. Hurst, "The problem of long-term storage in reservoirs," *International Association of Scientific Hydrology. Bulletin*, vol. 1, no. 3, pp. 13–27, 1956.

[32] B. B. Mandelbrot and J. R. Wallis, "Noah, Joseph, and operational hydrology," *Water Resources Research Series*, vol. 4, no. 5, pp. 909–918, 1968.

[33] B. B. Mandelbrot and J. R. Wallis, "Robustness of the rescaled range R/S in the measurement of noncyclic long run statistical dependence," *Water Resources Research Series*, vol. 5, no. 5, pp. 967–988, 1969.

[34] A. A. Anis and E. H. Lloyd, "The expected value of the adjusted rescaled Hurst range of independent normal summands," *Biometrika*, vol. 63, no. 1, pp. 111–116, 1976.

[35] C. S. Daw, C. E. A. Finney, and M. B. Kennel, "Symbolic approach for measuring temporal "irreversibility," *Physical Review A*, vol. 62, no. 2, pp. 1912–1921, 2000.

[36] P. H. Franses and H. Ghijsels, "Additive outliers, GARCH and forecasting volatility," *International Journal of Forecasting*, vol. 15, no. 1, pp. 1–9, 1999.

[37] N. Ebrahimi, E. Maasoumi, and E. S. Soofi, "Ordering univariate distributions by entropy and variance," *Journal of Econometrics*, vol. 90, no. 2, pp. 317–336, 1999.

[38] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, 1948.

[39] D. Freedman and P. Diaconis, "On the histogram as a density estimator: L2 theory," *Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete*, vol. 57, no. 4, pp. 453–476, 1981.

[40] D. W. Scott, "On optimal and data-based histograms," *Biometrika*, vol. 66, no. 3, pp. 605–610, 1979.
[41] C. Finney, K. Nguyen, C. S. Daw, and J. S. Halow, "Symbol-sequence statistics for monitoring fluidization," *Proceeding of the American Society of Mechanical Engineers*, vol. 5, pp. 405–411, 1998.
[42] S. Park, I. Kim, and K. Ahn, "A stochastic process for music: the example of K-pop music," *Journal of Physics: Conference Series*, vol. 2287, Article ID 012010, 2022.
[43] T. Schreiber, "Measuring information transfer," *Physical Review Letters*, vol. 85, no. 2, pp. 461–464, 2000.
[44] S. Jang, E. Yi, W. Kim, and K. Ahn, "Information flow between Bitcoin and other investment assets," *Entropy*, vol. 21, no. 11, Article ID 1116, 2019.
[45] S. Lee, E. Yi, Y. Cho, and K. Ahn, "The path to a sustainable palm oil futures market," *Energy Reports*, vol. 8, pp. 6543–6550, 2022.
[46] L. Sandoval Jr., "Structure of a global network of financial companies based on transfer entropy," *Entropy*, vol. 16, no. 8, pp. 4443–4482, 2014.
[47] K. Joo, M. Jeong, Y. Seo, J. H. Suh, and K. Ahn, "Shanghai crude oil futures: flagship or burst?" *Energy Reports*, vol. 7, pp. 4197–4204, 2021.
[48] S. Tzouras, C. Anagnostopoulos, and E. McCoy, "Financial time series modeling using the Hurst exponent," *Physica A: Statistical Mechanics and Its Applications*, vol. 425, pp. 50–68, 2015.
[49] G. M. Caporale, L. Gil-Alana, and A. Plastun, "Persistence in the cryptocurrency market," *Research in International Business and Finance*, vol. 46, pp. 141–148, 2018.
[50] A. W. Lo, "Long-term memory in stock market prices," *Econometrica*, vol. 59, no. 5, pp. 1279–1313, 1991.
[51] S. R. Bentes and R. Menezes, "Entropy: a new measure of stock market volatility?" *Journal of Physics: Conference Series*, vol. 394, Article ID 012033, 2012.
[52] L. Wang, K. Ahn, C. Kim, and C. Ha, "Agent-based models in financial market studies," *Journal of Physics: Conference Series*, vol. 1039, no. 1, Article ID 12022, 2018.
[53] K. Ahn, Y. Bi, and S. Sohn, "Price discovery among SSE 50 Index-based spot, futures, and options markets," *Journal of Futures Markets*, vol. 39, no. 2, pp. 238–259, 2019.
[54] E. Yi, Y. Cho, S. Sohn, and K. Ahn, "After the splits: information flow between Bitcoin and Bitcoin family," *Chaos, Solitons & Fractals*, vol. 142, Article ID 110464, 2021.
[55] X. Gabaix, "Power laws in economics and finance," *Annual Review of Economics*, vol. 1, no. 1, pp. 255–294, 2009.
[56] C. Kim, D. S. Kim, K. Ahn, and M. Y. Choi, "Dynamics of analyst forecasts and emergence of complexity: role of information disparity," *PLoS One*, vol. 12, no. 5, Article ID E0177071, 2017.
[57] E. Yi, K. Ahn, and M. Choi, "Cryptocurrency: not far from equilibrium," *Technological Forecasting and Social Change*, vol. 177, Article ID 121424, 2022.
[58] G. Ji, B. Dai, S. P. Park, and K. Ahn, "The origin of collective phenomena in firm sizes," *Chaos, Solitons & Fractals*, vol. 136, Article ID 109818, 2020.
[59] S. Begušić, Z. Kostanjčar, H. Eugene Stanley, and B. Podobnik, "Scaling properties of extreme price fluctuations in Bitcoin markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 510, pp. 400–406, 2018.
[60] P. Gopikrishnan, M. Meyer, L. Amaral, and H. Stanley, "Inverse cubic law for the distribution of stock price variations," *European Physical Journal B: Condensed Matter Physics*, vol. 3, no. 2, pp. 139-140, 1998.
[61] P. Gopikrishnan, V. Plerou, L. A. Nunes Amaral, M. Meyer, and H. E. Stanley, "Scaling of the distribution of fluctuations of financial market indices," *Physical Review E - Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics*, vol. 60, no. 5, pp. 5305–5316, 1999.
[62] X. Gabaix, P. Gopikrishnan, V. Plerou, and H. E. Stanley, "A theory of power-law distributions in financial market fluctuations," *Nature*, vol. 423, no. 6937, pp. 267–270, 2003.

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Research Article

Booms and Busts in Chinese Agricultural Markets: An Agent-Based Model

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This paper uses agent-based modelling to study the frequent booms and busts in Chinese agricultural markets. First, an artificial agricultural commodity market consisting of heterogeneous agents, such as producers, consumers, and speculators, is built. A numerical simulation suggests that speculation can cause large price fluctuations via nonlinear price dynamics. Then, parameters are estimated by the simulated method of moments using garlic and ginger price data in China from 2006Q2 to 2018Q3. The estimation yields a statistically significant speculative behavior parameter, supporting speculators' existence. Based on the well-estimated model, a low-cost policy experiment aiming at market stabilization is carried out. The essence of this policy is to release the theoretical steady state of the estimated model as the government-guided price to producers. The guided price, even partially followed by producers, can reduce simulated price variances and weaken speculators' negative impact on market stability. Robustness tests show that the effect of policy experiment is robust under a 20% change in any parameter value or a 5% change in the guided price.

1. Introduction

Booms and busts are frequently seen in Chinese agricultural markets. Though economists devote most of their attention to financial bubbles and crises in their research, large price fluctuations in financial markets fail to cause a direct impact on most Chinese households because of the low financial market participation rate in China [1]. By contrast, significant price changes in agricultural commodities usually hit almost all households in a direct and perceivable way, as agricultural products appear on the dining tables of every household daily. Therefore, booms and busts in Chinese agricultural markets are worth studying.

The reasons behind the large and persistent price changes of agricultural products are varied and multiform, including factors such as the weather [2], natural calamities, and livestock diseases. (Pork is a typical example of price booms and busts in China. The latest pork boom and bust happened from the beginning of 2019 to the end of 2021. The pork prices rose from 12 CNY/kg in January 2019 to 34 CNY/kg by the end of 2019, almost tripling within a year. The pork prices stayed at a high level throughout 2020, and then dropped from 36 CNY/kg in January 2021 to less than 11 CNY/kg by October 2021. It is widely acknowledged that the 2019–2020 pork bubble was directly caused by the African swine fever that swept across China in 2018 and 2019, leading to a considerable imbalance between market supply and demand. On January 8th, 2021, Dalian Commodity Exchange started trading live hogs, indicating the first future regarding the pork trade.) [3] Besides these natural causes, artificial factors such as market friction, inefficient supply chain, speculation, and others may also play a role in price changes. Figure 1 shows the detailed price trends of garlic and ginger in Chinese domestic markets from 2006 to 2018. Both prices had increased by more than five times from the lowest to the highest. The most considerable quarterly price changes were 83.68% in garlic and 69.46% in ginger. Chinese and international media reported them as the "garlic bubble" and "ginger bubble." Scholars argue that speculation is responsible for such agricultural price swings in China [4, 5]. In the present paper, we incorporate this factor into a theoretical model and explore a possible price stabilizing policy.

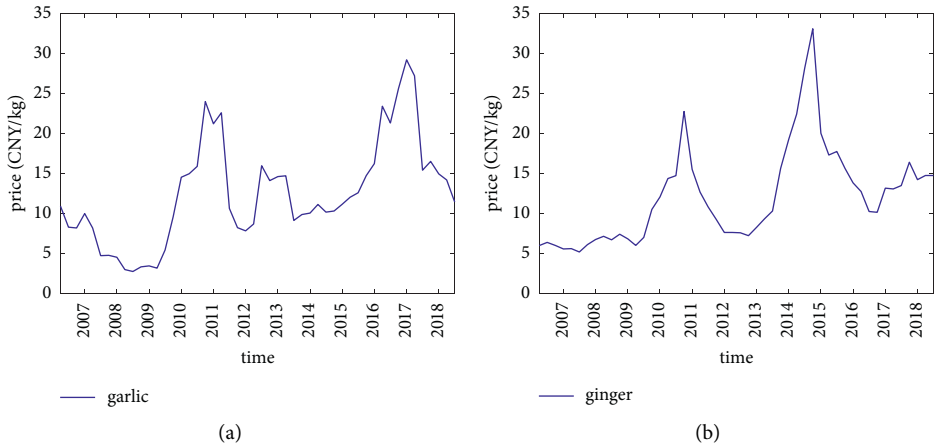

Figure 1: Quarterly price of garlic (a) and ginger (b) in China from 2006Q2 to 2018Q3.

Among so many kinds of agricultural commodities, one may ask why we chose to study garlic and ginger. Zhang et al. [6] point out that garlic and ginger have geographically concentrated origins, small market size, ease of storage, and less government intervention, making garlic and ginger easily manipulated by speculators. Moreover, until now, no agricultural future has taken garlic or ginger as the underlying commodity in domestic and international futures markets. Therefore, garlic and ginger markets can be treated as closed domestic markets in which the demand-supply relation and speculation play major roles in booms and busts. Furthermore, factors like the interaction between futures and spot prices and the risk transmission between Chinese and international futures markets do not exist. (As a comparison, agricultural products with well-developed futures include soybeans, corn, and wheat. The existence of well-developed futures markets can be a double-edged sword. On the one hand, corresponding futures can hedge against large price fluctuations in the future, therefore stabilizing spot prices. On the other hand, fluctuations of future prices in the international market may propagate to the domestic market, destabilizing domestic spot prices. When analyzing booms and busts in these markets, the interaction between spot and future prices and the interaction between domestic and international futures markets cannot be ignored. A new model that covers these interactions needs to be developed.)

Researchers call price bubbles fueled by speculative activity "speculative bubbles." Previous literature on speculative bubbles in agricultural commodity markets mainly concentrates on detecting speculative bubbles by using methods such as the supremum Augmented Dickey–Fuller test [7], duration dependence test [8], and momentum threshold autoregressive approach [9]. Gilbert [7] finds speculative bubbles in soybeans from 2006 to 2008, but not in corn and wheat. Li et al. [4] find speculative bubbles in most Chinese agricultural commodity futures markets from 2006 to 2014. Based on these empirical works, we embed speculators into our model without questioning their existence.

Since drastic price fluctuations of agricultural products negatively influence households' daily living and market expectations, arousing extensive social concern in China, agricultural commodity price stabilization has attracted the attention of policymakers and researchers. Studies on price stabilizing policies in agricultural markets primarily focus on their microeconomic benefits [10, 11]. The price stability of agricultural commodities is critical to the stability of producer incomes and consumer expenditures [10]. Massell [11] shows that price stabilization increases social welfare through a positive change in the sum of producer and consumer surplus. Despite the theoretical desirability of improved stability, stabilization policies commonly used in practice, e.g., price limiters such as price ceilings or floors, have a few disadvantages. For instance, an inappropriately high price floor may result in overproduction [12]. Price limiters can also generate substantial fiscal costs due to maintaining a buffer stock [13]. Therefore, it is essential to explore new options.

Studies most relevant to our work incorporate speculators as a destabilizing force in agent-based models (ABMs) of commodity markets. He and Westerhoff [14] built a log-linear commodity market model composed of producers, consumers, and speculators. They investigated the influence of conditional price limiters jumping between bottoming and topping limits on model price dynamics, finding that the conditional price limiters efficiently reduce these fluctuations. Westerhoff and Wieland [15] developed a behavioral cobweb model with linear supply and demand and speculators who can switch between fundamental and technical trading rules. Variations in the number of speculators cause price bifurcations. Though speculators are destabilizing the market on average, they can stabilize prices in certain situations, and thus banning them from trading commodities is not necessarily wise. Fernandez-Mena et al. [16] built an ABM to study the flows in agro-food networks. They simulated material exchanges for a small region in France and found that the number of flows is sensitive to distance and shared interest between agents.

This paper develops and estimates an ABM of agricultural commodities to study the impact of speculation on price stability. Three kinds of heterogeneous agents participate in the market: producers, consumers, and speculators. On the supply side, producers have linear backward-looking expectations and an S-shaped production function. Consumers with rational

expectations and speculators with extrapolative expectations coexist on the demand side. A theoretical model analysis suggests speculation may indirectly cause endogenous price fluctuations by influencing producers' expectations. Using the simulated method of moments (SMM) estimation and quarterly garlic and ginger prices in China from 2006Q2 to 2018Q3, our model suitably captures empirical price features. The significance of speculators' trend extrapolating parameter implies that their speculative demand nourishes the garlic and ginger bubbles. Then, based on the well-estimated model, a low-cost price stabilizing policy experiment is conducted. The proposed policy reveals the estimated model's theoretical steady states as the government-guided prices to producers. When a portion of producers uses the guided prices to replace their original expectations, they adjust their production and supply accordingly. Via market clearance, the speculators' impact on market prices is weakened, the simulated price variance drops, and the market stability improves.

The rest of this paper is organized as follows: Sections 2 builds an agent-based model and discuss its nonlinear price dynamics. Section 3 estimates the model by the simulated method of moments. In Section 4, a price stabilizing policy experiment is conducted. The robustness of policy experiment is tested in Section 5. Finally, conclusions and policy implications are proposed in Section 6.

2. Agent-Based Modelling

The method of ABMs first appeared in the 1970s and started flourishing in the 1990s when the computing power of computers sharply increased. The most significant feature of such models is the existence of multiple heterogeneous agents representing economic subjects, whose behavior is designed to mimic human subjects. When ABMs are used to study macroeconomic problems or financial markets, the bottom-up structure of ABMs naturally bridges microeconomics and macroeconomics. After more than 30 years of rapid development, there are several handbooks and collections of works reviewing ABMs comprehensively. Please refer to Tesfatsion and Judd [17] and Hommes and LeBaron [18] for more information.

This section designs a simple ABM for an agricultural commodity and derives a degenerate case of the model without the presence of speculators. Figure 1 shows that the garlic and ginger bubbles grew and burst over the years, implying that these bubbles are beyond the explanation of seasonal factors and production cycles. Natural cyclical factors in the production of agricultural products are neglected, and artificial factors, such as decision-making by market participants and trading among participants, are emphasized to ensure that the proposed model focuses on the impact of speculation on market prices. Section 2 ends with a comparison between the numerical results of the original ABM and the degenerate case.

2.1. Heterogeneous Agents and Market Clearance. In the proposed ABM, the artificial market is filled with three kinds of heterogeneous agents: producers, consumers, and speculators, shown by a superscript P, C, and S, respectively. At each period t, heterogeneous agents first update their expectations. Producers, consumers, and speculators' expectations are denoted as $P^P_{e,t}$, $P^C_{e,t}$, and $P^S_{e,t}$. Agents' expectations are updated according to the following rules:

$$P^P_{e,t} = wP_{t-1} + (1-w)P_{t-2}, 0 < w < 1, \tag{1}$$

$$P^C_{e,t} = P_t, \tag{2}$$

$$P^S_{e,t} = P_{t-1} + \gamma\left(P_{t-1} - P_{t-2}\right),\ \gamma > 0. \tag{3}$$

Producers have linear backward-looking expectations [19]. $P^P_{e,t}$ is the weighted average of the past two periods prices. Parameter w measures the weight of P_{t-1} in the producers' expectations. Consumers have rational expectations (The rationale behind this assumption is that consumption decisions tend to be made more quickly and easily compared to the time and effort the production process takes. We provide an example, the reference prices usually seen in some farmers' markets in China, and some discussion in the last section.), and $P^C_{e,t}$ is not adaptively formed using past information. Speculators form $P^S_{e,t}$ by extrapolating past price trends. The larger γ is, the more intense the extrapolation is. After the expectations are updated, agents then decide the amount to supply or purchase. An S-shaped supply schedule is adopted, which is appropriate if fixed costs are high at low output levels and capacity constraints come into force at high output levels [20]. The producers' supply is expressed as follows:

$$S_t = \arctan\left(c\left(P^P_{e,t} - d\right)\right) + e. \tag{4}$$

The consumption demand D^C_t is linear in the consumers' expected price of period t, while speculative demand D^S_t is linear in speculator's expected price of period $t+1$.

$$D^C_t = a - bP^C_{e,t}, \tag{5}$$

$$D^S_t = a - bP^S_{e,t+1}. \tag{6}$$

The market clears when the total supply S_t intersects with the total demand D_t. The total demand is the weighted sum of the consumption demand and speculative demand.

$$S_t = D_t, \tag{7}$$

$$D_t = N_t D^C_t + \left(1 - N_t\right)D^S_t. \tag{8}$$

Here, N_t is the fraction of consumers, and $1 - N_t$ is the fraction of speculators. The switching of buyers between the consumption motive and speculative motive follows the Brock and Hommes [21]. N_t can be expressed as the following multinomial logistic model:

$$N_t = \frac{e^{\varepsilon\pi^C_{t-1}}}{e^{\varepsilon\pi^C_{t-1}} + e^{\varepsilon\pi^S_{t-1}}}. \tag{9}$$

If $\varepsilon > 0$, the share of speculators is a monotonic increasing function of π^S_t, which is the performance measure of speculators. Speculators consider the commodity as a financial asset, so their performance measure equals the

capital gain in (10), where R is the gross risk-free rate. Consumers' performance measures are set to 0.

$$\pi_t^S = (P_t - RP_{t-1})D_{t-1}^S, \tag{10}$$

$$\pi_t^C = 0. \tag{11}$$

Equations (1)–(11) constitute the ABM for the agricultural commodity. The steady-state price P^* for the model satisfies that

$$\arctan(c(P^* - d)) + bP^* = a - e. \tag{12}$$

2.2. Degenerate Case without Speculators. A degenerate case of the ABM is now considered, where $\gamma > 0$ is violated and γ becomes zero. Speculators' expectations, represented by (3), becomes

$$P_{e,t}^S = P_{t-1}. \tag{13}$$

Demand originated from speculators, represented by (6), becomes

$$D_t^S = a - bP_{e,t+1}^S = a - bP_t. \tag{14}$$

Because (14) and the consumption demand in (5) are identical, one may conclude there is no speculation when $\gamma = 0$. The degenerate case is written as follows:

$$\begin{cases} P_{e,t}^C = P_t, \\ P_{e,t}^P = wP_{t-1} + (1-w)P_{t-2}, 0 < w < 1, \\ S_t = \arctan\left(c\left(P_{e,t}^P - d\right)\right) + e, \\ D_t^C = a - bP_{e,t}^C, \\ S_t = D_t^C. \end{cases} \tag{15}$$

2.3. Price Dynamics with and without Speculators. To unveil the channel through which speculation may induce price fluctuations, the original ABM and the degenerate case are investigated numerically, and their results are compared.

Figure 2 presents the bifurcation diagrams of w drawn using the following parameter set: $a = 8$, $b = 0.44$, $c = 2$, $d = 9.6$, $e = 1.5$, $\gamma = 0.089$, $\varepsilon = 0$, and $R = 1.0186$. The values of γ, ε, and R only apply to the original ABM. The results of the original ABM are shown in Figure 2(a), while the results of the degenerate case are provided in Figure 2(b).

3. Estimation

This section estimates (Please see Hansen and Heckman [23] and Kydland and Prescott [24] for model estimation and calibration. Chen et al. [25] compare several methods widely used in model estimation.) the model via simulated method of moments (SMM) by using the ABM as an artificial laboratory to scrutinize the effects of potential stabilization policies on China's agricultural commodity price. Subsection 3.1 briefly introduces the estimation methodology and the data used. Subsection 3.2 presents the estimation results.

3.1. Simulated Method of Moments. Using the SMM approach [26, 27], where the core idea is to match model-generated moments with empirical moments, the parameter vector $\theta \equiv \{a, b, c, d, e, w, \gamma, \varepsilon, \sigma\}$ is estimated, where σ is the standard deviation of the noise term used in simulations. Here, $R = 1.0186$ to yield a reasonable gross risk-free rate. This paper uses a sample composed of quarterly price data (Data source: http://www.chinabric.com) of the two commodities from 2006Q2 to 2018Q3 to justify the argument that speculation is responsible for garlic and ginger price instability in China. Each time series has $N = 50$ observations, let $\hat{m}$ be the moment vector of model-generated log returns, computed based on $K = 200$ simulations of N observations. Let m be its empirical counterpart. Formally, the SMM estimator of θ is expressed as

$$\hat{\theta}_{SMM} = \arg\min J(\theta), \tag{16}$$

$$J(\theta) = \frac{NK}{1+K}(\hat{m}(\theta) - m)^T W (\hat{m}(\theta) - m), \tag{17}$$

where W is a positive definite weighting matrix. To ensure the efficiency of the estimation results, the optimal W is the inverse of the variance-covariance matrix of $(\hat{m}(\theta_{true}) - m)$ [28]. θ_{true} is a vector of true values of unknown parameters.

The optimal weighting matrix is approximated via a two-step variance-covariance estimator. First, we use an identity matrix as the weighting matrix (i.e., $W = I$) and minimize the objective function to get a preliminary SMM parameter vector $\hat{\theta}_1$.

$$\hat{\theta}_1 = \arg\min \frac{NK}{1+K}(\hat{m}(\theta) - m)^T I (\hat{m}(\theta) - m). \tag{18}$$

Then, we employ $\hat{\theta}_1$ to conduct simulations and compute the variance-covariance matrix of $(\hat{m}(\hat{\theta}_1) - m)$, denoted as $\hat{\Omega}$. The estimate of the optimal weighting matrix is obtained by further taking the inverse of matrix $\hat{\Omega}$.

$$\begin{aligned} \hat{\Omega} &= \frac{1}{N}\left(\hat{m}\left(\hat{\theta}_1\right) - m\right)\left(\hat{m}\left(\hat{\theta}_1\right) - m\right)^T, \\ W^* &= \hat{\Omega}^{-1}. \end{aligned} \tag{19}$$

3.2. Parameter Estimates and Interpretations. By interpreting the estimation results, the impacts of speculation on price dynamics in China's garlic and ginger market are inspected. Table 1 summarizes the estimated parameters of the garlic and ginger markets. Table 2 presents the simulated moments generated after the model estimation and their empirical counterparts.

The results in Table 1 can be interpreted as follows. The J statistic in (17) has an asymptotic chi-square distribution with 1 degree of freedom. The J statistic for garlic is 0.3379, and the J statistic for ginger is 0.2959. The critical value of $\chi 2(1)$ at a 95%

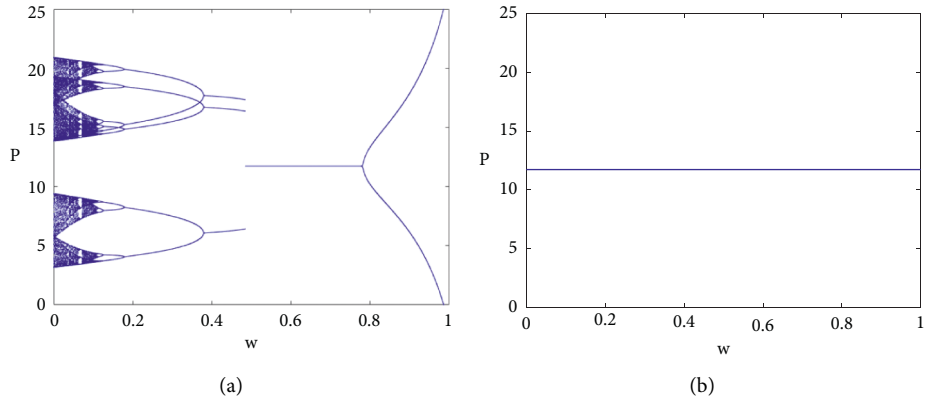

FIGURE 2: Bifurcation diagrams of the parameter w, with all other parameters fixed at a = 8, b = 0.44, c = 2, d = 9.6, e = 1.5, $\gamma = 0.089$, $\varepsilon = 0$, and R = 1.0186. The figures show the existence of single or multiple stable steady states or even chaotic price dynamics under different w-values. The w appears in (1) and (15), denoting the weight of the latest market price in producers' price expectation formation. (a) In the original ABM with speculators, nonlinear price dynamics show various phenomena, such as pitch-fork bifurcation (w = 0.7703), period-doubling bifurcation (0.109 < w < 0.3812), and chaos (w < 0.1098). (b) In the degenerate case without speculators, one single stable steady state of the market price exists under different values of w.

confidence level is 3.84, and the p values corresponding to the two test statistics are 0.5610 and 0.5865. The model is neither rejected by thedata of garlic nor by the data of ginger. Despite the small J statistics, to conclude that the real-life price dynamics of garlic and ginger are well captured by the ABM proposed and driven by speculation, the possibility that $\gamma = 0$ also needs to be ruled out. If the estimated γ is not significantly different from 0, the true data generating process may be closer to the non-speculation degenerate case given by (15). The estimated values of γ turn out to be significantly positive and are 0.4182 for garlic and 0.5497 for ginger. Since the parameter γ represents extrapolation strength, a comparison of the parameter values of ginger and garlic shows that ginger speculators have a slightly stronger belief about trend continuation than garlic speculators. The original ABM is favored over the degenerate case by empirical data, denoting that there exists a speculative demand in China's garlic and ginger market. Since speculation indirectly destabilizes prices by influencing producers' expectations in the original ABM, the nonrejection J statistics accompanied by the statistical significance of the estimated γ imply a causal relationship between speculative activities and the excessive price volatility of the two commodities.

Parameter ε is usually called the intensity of choice in ABMs [21], and literature shows that this parameter plays an important role in increasing model complexity [29]. It reveals the herding behavior of buyers between the consumption motive and speculative motive. According to (9), $1-N_t$ measures how the fraction of speculators at the market demand side evolves with past speculative payoffs: when $\varepsilon = 0$, the fraction of speculators is fixed at a constant level; when $\varepsilon > 0$, a larger positive past speculative payoff attracts more buyers to the speculative motive; when $\varepsilon = +\infty$, buyers are extremely sensitive to positive speculative payoffs, and any positive payoffs can drive all buyers to switch to the speculative motive; and when $\varepsilon < 0$, a negative past speculative payoff makes buyers irrationally switch away from speculative motive. A negative ε does not make any economic sense. With a 1% significance level, ε is estimated as 0.5231 for garlic and 3.3853 for ginger, suggesting the existence of herding behavior among buyers in both markets. Both the share of garlic speculators and ginger speculators increase with positive past speculative payoffs. As a comparison of parameter values, buyers' herding behavior in the ginger market is stronger than buyers' herding behavior in the garlic market.

The supply side and producer behaviors will now be addressed. The estimated values of w are 0.2395 for garlic and 0.3523 for ginger, both significant at the 1% level. According to (1), producers in both markets hold linear backward-looking expectations to some extent. Their expectations for the newest market price are weighted averages of historical prices at the latest two periods. The only difference between producers' expectations is that ginger producers put more weight (0.3523) on the latest price than the garlic producers (0.2395).

Because of space limitations, the present paper does not further interpret other parameters estimated in Table 1. The estimation results indicate that the real-world price dynamics of the two agricultural commodities are adequately captured by the proposed model, and speculation is a possible driving force behind excessive price volatility in China's garlic and ginger markets.

Figure 3(a) shows that the enaction of the policy barely alters the intensity of speculative activities for the two agricultural commodities. In the top panel of Figure 3(a), after policy application, the average share of garlic speculators does not deviate too far away from its prior-policy value of 0.1917 as h, the proportion of producers following government-guided price, varies between 0 and 1. In the bottom panel of Figure 3(a), after policy application, the average share of ginger speculators boundedly fluctuates between 0.3170 and 0.3929 as h varies between 0 and 1, compared with a prior-policy value of 0.3431. Because the government-guidance price policy is merely imposed on producers, this policy does not intervene in speculative activities directly, and the

Table 1: SMM estimated parameters for garlic and ginger.

	Garlic				Ginger		
a	8.5142*** (0.0098)	w	0.2395*** (0.0075)	a	11.4282*** (0.0913)	w	0.3523*** (0.0277)
b	0.3619* (0.1611)	γ	0.4182* (0.1979)	b	0.0694*** (0.0250)	γ	0.5497*** (0.1541)
c	3.0010*** (0.7862)	ε	0.5231*** (0.0005)	c	1.9924*** (0.0150)	ε	3.3853*** (0.0311)
d	9.6978*** (1.3307)	σ	1.0154*** (0.2932)	d	9.6863 (5.0438)	σ	0.7885* (0.3746)
e	1.3786*** (0.0145)	J	0.3379	e	−1.2438*** (0.0010)	J	0.2959

Note.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, standard errors in parentheses.

Table 2: Sample moments and simulated moments of return series.

	Garlic		Ginger	
Moments	Sample	Simulated	Sample	Simulated
Mean	1.005654	1.012601	0.999997	1.003528
Variance	0.015937	0.019276	0.006618	0.002608
Skewness	1.104322	1.090279	0.391738	0.391610
Kurtosis	4.356395	4.335239	2.465169	2.465194
$\mathrm{Cov}(r_t, r_{t-1})$	0.006836	0.007562	0.003036	0.006368
$\mathrm{Cov}(r_t, r_{t-2})$	0.002303	0.001825	0.001374	0.001931
$\mathrm{Cov}(r_t, r_{t-3})$	0.000946	0.000251	0.000394	0.000493
$E(r_t^2.r_{t-1}^2)$	1.086123	1.047242	1.021625	1.024045
$E(r_t^2.r_{t-2}^2)$	1.067539	1.075341	1.012052	1.013522
$E(r_t^2.r_{t-3}^2)$	1.060742	1.079454	1.007846	1.013871

average market fraction of speculators shows no visible reaction to the policy implementation.

Figure 3(b) shows that the policy leads to an apparent reduction in the simulated average price variances of the two agricultural commodities. Increases in h, either in the garlic or ginger markets, further enlarge the reduction. Generally speaking, the larger the proportion of producers who follow the policy, the smaller the average price volatility becomes. More specifically, in the top panel of Figure 3(b), when h increases from 0 to 1, the garlic price variance almost monotonically decreases from 65.71 to 9.09. In the bottom panel of Figure 3(b), when h increases from 0 to 0.8312, the ginger price variance drastically decreases from 53.47 to 16.06; when h becomes greater than 0.8312, the level of the ginger price variance remains relatively unchanged

Recall that speculation indirectly destabilizes agricultural commodity prices by influencing producers' price expectations. While the policy discussed is unintended and unable to reduce the speculator proportion, it still significantly weakens speculators' negative impact on price stability by protecting producers' price expectations from manipulating speculative activities. When more producers follow the policy, more producers are prevented from adopting the misleading price signals sent by speculators to form producers' price expectations. Therefore, it is unsurprising that an overall negative relationship between h and simulated price variances is presented. In other words, the government-guidance price policy weakens the price expectation formation channel through which speculators can influence market price volatility.

4. A Price Stabilizing Policy Experiment

In this section, a policy experiment is carried out to explore the feasibility of a low-cost price stabilization policy using the estimation results of garlic and ginger as the empirical microfoundation. Speculation may indirectly cause endogenous price fluctuations by facilitating the destabilizing force of producers' expectations; thus, it might be possible for a central authority to weaken the speculators' impact on the market by guiding producers' expectations.

The intervention strategy reveals a government guidance price to producers. The government-guided price equals the theoretical steady-state price P^*. Because some producers may not necessarily trust the central authority or miss the information released by it, the present paper assumes that a fraction h of producers uses the government-guided price to replace their original linear backward-looking expectations. The price expectation of those who follow the policy is denoted as $P_{e,t}^G$. The new total supply is given by (22).

$$P_{e,t}^G = P^*, \tag{20}$$

$$\begin{aligned} S_t = {} & h\left(\arctan\left(c\left(P_{e,t}^G - d\right)\right) + e\right) \\ & + (1-h)\left(\arctan\left(c\left(P_{e,t}^P - d\right)\right) + e\right). \end{aligned} \tag{21}$$

Other setups of the ABM remain unchanged. In the simulations, parameters other than h are assigned the estimated values. The parameter setting of the garlic market is $a = 8.5142$, $b = 0.3619$, $c = 3.0010$, $d = 9.6978$, $e = 1.3786$, $w = 0.2395$, $\gamma = 0.4182$, and $\varepsilon = 0.5231$. The parameter setting of the ginger market is $a = 11.4282$, $b = 0.0694$, $c = 1.9924$, $d = 9.6863$, $e = -1.2438$, $w = 0.2395$, $\gamma = 0.5497$, and $\varepsilon = 3.3853$. Parameter h increases with a minimal increment step of 0.01. Each simulation lasts $T = 5000$ periods. For each parameter combination, the following two statistics are calculated:

The average market fraction of speculators is monitored by calculating the following:

$$\text{weight } S = \frac{1}{T}\sum_{t=1}^{T}(1 - N_t). \tag{22}$$

The price volatility is measured by the sample variance of the simulated price series.

$$\text{volatility} = \frac{1}{T-1}\sum_{t=1}^{T}(P_t - \overline{P})^2. \tag{23}$$

The government-guidance price is a low-cost policy because it is suggestive rather than mandatory. The central authority needs to properly calculate and release the guided price to producers rather than force producers to follow the guided price strictly. As this policy is suggestive, it is inevitable that some producers will decide to follow it while

others will not due to different reasons. The parameter h denotes the fraction of producers who follow the government-guided price in their production decision-making process. This parameter is directly related to the breadth of the policy acceptance. Therefore, the analysis of the policy experiment focuses on the parameter h.

Figure 3 illustrates how the average speculator fraction and average price volatility in the garlic and ginger markets react to the introduction of the government-guidance price policy. The dashed lines represent values of the two statistics before policy implementation, and the solid lines represent values of the two statistics after policy implementation.

Recall that variations in parameter w represent the weight of the latest market price in producers' price expectation formation in (1). The larger (smaller) w is, the greater weight producers place on the price of the previous (penultimate) period. In the original ABM with speculation, shown as the panel (a) of Figure 2, changes in the producers' expectations can influence the occurrence and amplitudes of price fluctuations under the parameter set $a = 8$, $b = 0.44$, $c = 2$, $d = 9.6$, $e = 1.5$, $\gamma = 0.089$, $\varepsilon = 0$, and $R = 1.0186$. More specifically, when $0.4843 < w < 0.7703$, prices generated by the ABM stay in the stable steady state at $P^* = 11.7274$ after the transient periods. If w increases or decreases beyond the interval, the steady state loses its stability, and endogenous price fluctuations arise. At $w = 0.7703$, a pitch-fork bifurcation occurs and two stable steady states start to coexist. As w further increases, the two stable steady states diverge. At $w = 0.4843$, one stable steady state slips into three stable steady states. As w decreases, period-doubling bifurcations simultaneously occur at all three branches at $w = 0.3812$. As w further decreases, more period-doubling bifurcations occur repeatedly. For $w < 0.1098$, the price dynamics exhibit chaotic behavior. In the degenerate case without speculation, shown in the panel (b) of Figure 2, the bifurcation diagrams of w are just one horizontal straight line, implying that producers' expectation changes do not give rise to price volatility changes under the same parameter set.

The features of nonlinear price dynamics determine market price stability. When only one stable steady state exists, the market price can quickly converge to the steady state and remain there. If perturbations or exogenous shocks bring the price away from the steady state, the system can go back to the steady state automatically after the perturbations or exogenous shocks disappear. When multiple stable steady states coexist, starting from any initial price level, to which stable steady state the system will eventually evolved into depends on the attracting basin of each steady state. After the system reaches any stable steady state, any tiny perturbation may trigger the price jump from the old stable steady state to a new one. When the system shows chaotic behavior, the system exhibits what is called sensitive dependence on initial conditions. Any slight discrepancy in two initial price levels can lead to huge differences in later price time series. The price time series do not converge to any price level but may show up at any price level within a bounded domain. Because of space limitations, the present paper will not elaborate further on this issue. For more information on bifurcations and nonlinear dynamics, please refer to Strogatz [22].

Figure 2 shows the nonlinear price dynamics of the original ABM and the existence of one stable steady state in the degenerate case. The comparison of the price dynamics of those two cases, one with and the other without speculation, lays the theoretical foundation of the posited argument that speculation can endogenously cause large agricultural price fluctuations in price time series since multiple steady states, or even chaotic price behaviors, exist. The comparison in Figure 2 is based on a specific parameter set. Similar comparisons can be conducted under other parameter sets.

5. Robustness Tests

This section examines the robustness of the proposed policy's effects under different model parameters or government-guided price levels. The rationale behind such robustness tests is that, if the central authority adopts alternative estimation methods or their calculation ability is limited, so that their model estimates or guided prices deviate from our calculations, how will the deviations affect the policy's effects. Will the policy experiment still lead to a price variance reduction when parameter estimates or guided prices vary within reasonable ranges?

In the combination of a, b, c, d, e, w, γ, ε, and $P^G_{e,t}$, only one parameter or the guided price is tested at a time, and others are all fixed at the values used in Section 4. When a parameter or the guided price is tested, its value deviates from the value used in Section 4 by a given percentage, for example $\pm$ 5% or $\pm$ 20%. For each alternative combination of a, b, c, d, e, w, γ, ε, and $P^G_{e,t}$, this section runs a policy experiment similar to the one in Section 4 with a fixed $h = 0.5$, showing that the guided price is followed by 50% of producers.

Table 3 reports the resulting ratios of $\mathrm{Var}(P_{\text{no intervention}}) - \mathrm{Var}(P_{\text{intervention}})$ to $\mathrm{Var}(P_{\text{no intervention}})$, for which a positive value represents a price variance reduction and a negative value represents a price variance increase after the intervention. Table 3 suggests that the price stabilizing effects of the government-guided policy are reasonably robust. In the original policy experiment conducted in Section 4, the price variance reduction ratio caused by half of producers following the guided price is 15.46% in the garlic market and 50.60% in the ginger market, shown in Figure 3(b) when h is 0.5. As a comparison, if a parameter changes by –5% or +5% from its estimated value, the price variance reduction ratio varies from 12.28% to 15.02% or from 9.60% to 18.11% in the garlic market and from 50.07% to 51.33% or from 45.71% to 55.11% in the ginger market. The proposed policy's effects is robust under a 5% change of any parameter in both markets. If a parameter changes by –20% or +20%, the price variance reduction ratio deviates more from 15.46% in the garlic market and 50.60% in the ginger market. Nevertheless, all price variance reduction ratios are positive, showing effects of price variance reduction under a 20% change of any parameter in both markets.

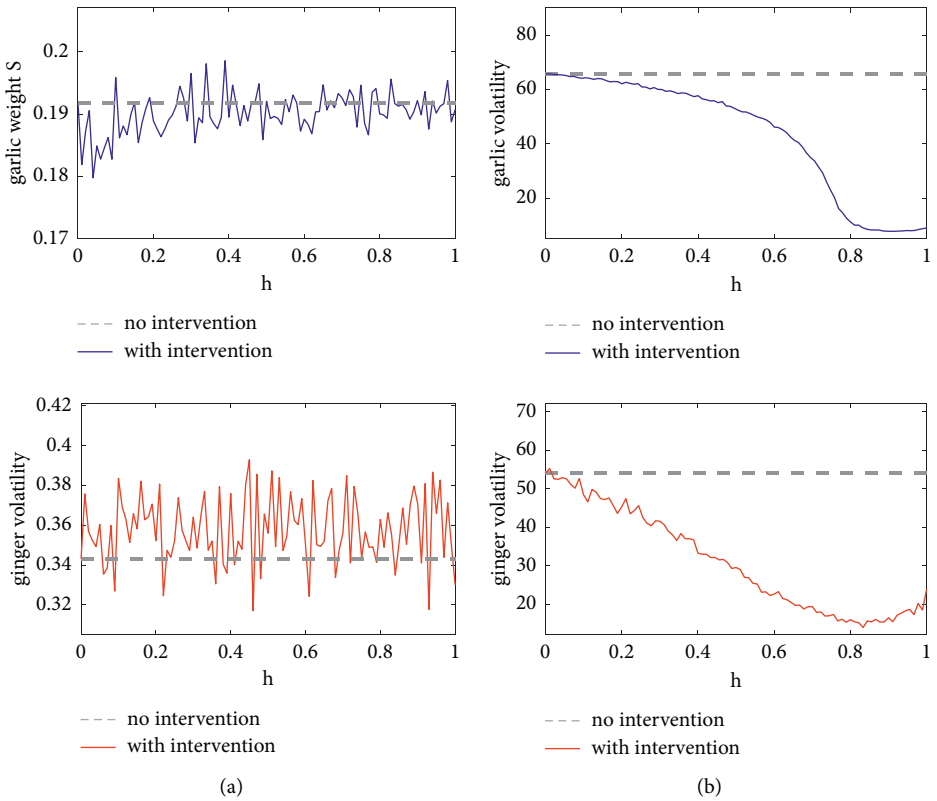

Figure 3: Intervention results of the government-guidance price policy. The figures show the average market fraction of speculators (weight S) and average price volatilities under different proportions of producers following government-guided price (parameter h). (a): The average market fraction of speculators is barely affected by the parameter h. (b): More producers following the government-guided price help to reduce price volatility.

Table 3: Price variance reductions due to intervention under alternative settings.

	Garlic				Ginger			
	Model parameter or $P_{e,t}^G$ varies by				Model parameter or $P_{e,t}^G$ varies by			
	−5 %	+5%	−20%	+20%	−5%	+5%	−20%	+20%
a	12.44%	11.92%	6.06%	19.98%	50.22%	50.79%	48.29%	38.42%
b	14.76%	9.60%	16.98%	12.48%	51.07%	45.71%	67.41%	48.94%
c	13.87%	10.58%	22.67%	4.22%	50.66%	50.36%	36.17%	46.12%
d	13.78%	15.26%	40.63%	24.72%	50.29%	50.51%	53.03%	50.71%
e	12.28%	13.94%	29.47%	39.12%	51.33%	52.65%	63.13%	77.22%
w	12.66%	16.94%	43.89%	1.87%	50.07%	55.11%	82.62%	25.18%
γ	15.02%	11.14%	13.91%	26.83%	50.51%	50.28%	46.06%	68.19%
ε	14.39%	18.11%	11.58%	33.56%	50.52%	50.93%	49.14%	55.26%
$P_{e,t}^G$	15.73%	13.92%	−3.31%	−39.12%	55.45%	50.57%	3.28%	−1.46%

The last row of Table 3 presents the results when the government-guided prices differ from the values used in Section 4. When the guided price changes by −5% or +5%, the price variance reduction ratio is 15.73% or 13.92% in the garlic market and 55.45% or 50.57% in the ginger market, comparing with the initial 15.46% in the garlic market and 50.60% in the ginger market. The policy's effects are robust under a 5% miscalculation of the guided price. However, the central authority's obviously incorrect calculation of the guided price could lead to an ineffective intervention. If the guided price changes by −20% from the stable steady state, the garlic price variance increases by 3.31% and the ginger price variance decreases by 3.28%. If the guided price changes by +20% from the stable steady state, the garlic price variance increases by 39.12%, and the ginger price variance increases by 1.46%. The government-guided price policy loses its efficacy under a 20% miscalculation of the guided price.

As a comparison between parameters and the guided price, it seems that the model result is more sensitive to the guided price. A comparison between garlic and ginger markets show that the model result is more robust in the ginger market.

6. Conclusions and Policy Implications

This paper develops and estimates an agent-based model filled with producers, consumers, and speculators to understand the role of speculation in market price dynamics and explore a low-cost price stabilizing policy. On the supply side, producers plan their production according to their price expectations. On the demand side, consumers and speculators coexist, and herding behavior driven by past speculative payoffs among buyers is allowed. A theoretical analysis of the model's nonlinear price dynamics shows that speculation can cause multiple steady states or even chaotic price behavior, destabilizing market prices. The model is estimated by the simulated method of moments and quarterly prices of garlic and ginger in China from 2006Q2 to 2018Q3. The model estimation results suggest that our model properly captures price dynamics in the garlic and ginger markets. Chinese garlic and ginger producers make production plans according to linear backward-looking expectations of product prices. The significant estimates of speculators' trend-extrapolating parameters verify the existence of speculative demand for garlic and ginger and provide evidence supporting speculation-driven price volatilities. In the policy experiment conducted upon the estimated model, we design a low-cost policy of releasing the theoretical steady-state price of the estimated model as a government-guided price to producers. This suggestive policy works through the supply side. When producers replace their old backward-looking expectations with the guided price, their output levels are adjusted accordingly, the product prices achieve market clearance change, and the simulated price variances of garlic and ginger drop. A larger fraction of producers following the policy positively correlates to lower simulated variances of garlic and ginger prices. Though such a supply-side policy barely reduces the average market fraction of speculators on the demand side, it decreases speculators' negative impact on market stability.

In the current model, speculators only participate on the demand side. In practice, speculators can also appear on the supply side. Future work should treat speculators as intermediaries involved in both the supply and demand sides. Besides, since the empirical data of product outputs are available, an agent-based model which integrates such data into simulation and estimation would be more convincing.

The government-guided price policy proposed in this paper is different from the reference prices usually seen in some farmers' markets in China. The former aims to guide farmers' production process, while the latter promotes fair trading between sellers and consumers. The reference prices in farmers' markets work by reducing the information asymmetry of market trading in local markets. They are provided by market managers and updated almost daily or at least weekly. Bargaining between individual sellers and consumers happens all the time. However, trading prices usually do not deviate much from reference prices. This phenomenon is the rationale behind the assumption of our model that the consumers' expectation is consistent with the market price. With the help of reference prices and other information, consumption decisions tend to be made more quickly and easily compared to the time and effort the production process takes. The government-guided price policy proposed in this paper reduces the asymmetric information producers faced in the domestic market. The central government utilizes its information collection and calculation ability to help producers make more reasonable output plans and, therefore, better allocate their factors to the production of multiple agricultural commodities.

In the last few years, futures markets have quickly developed in China. An increasing number of agricultural products are taken as the underlying commodities of new futures. The introduction of corresponding futures satisfies the needs for hedging from the market demand side and helps to stabilize spot markets to some extent. Besides garlic and ginger, pork is a typical example of price booms and busts in China, although pork cycles are usually affected by swine fever. The latest pork bubble occurred in 2019 and 2020. Since the beginning of 2021, Dalian Commodity Exchange started trading live hogs. Pork prices dropped from 36 CNY/kg in January 2021 to less than 11 CNY/kg by October 2021. The introduction of live hog futures helped to burst the 2019–2020 pork bubble, demonstrating a positive example of futures stabilizing spot markets. Moreover, similar to apples and red dates, which already have corresponding futures traded in Zhengzhou Commodity Exchange, garlic and ginger are self-sufficient within the domestic market; there is no need to worry about risk transmission from international spot and futures markets. If possible, domestic commodity exchanges should seriously consider introducing new futures on garlic and ginger after a comprehensive investigation of market demand for such futures and a cost-benefit analysis. Before that, the low-cost government-guided price policy proposed in this paper is a worthy endeavor.

Data Availability

Empirical data are publicly available at http://www.chinabric.com. The simulated data and simulation codes can be obtained from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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References

[1] Z. Yin, Y. Wu, and L. Gan, "Financial availability, financial market participation and household portfolio choice," *Economic Research Journal*, vol. 3, pp. 87–99, 2015.

[2] R. Roll, "Orange juice and weather," *The American Economic Review*, vol. 74, no. 5, pp. 861–880, 1984.

[3] S. You, T. Liu, M. Zhang et al., "African swine fever outbreaks in China led to gross domestic product and economic losses," *Nature Food*, vol. 2, no. 10, pp. 802–808, 2021.

[4] J. Li, J. P. Chavas, X. L. Etienne, and C. Li, "Commodity price bubbles and macroeconomics: evidence from the Chinese agricultural markets," *Agricultural Economics*, vol. 48, no. 6, pp. 755–768, 2017.

[5] X. Miao, B. Yu, B. Xi, and Y. H. Tang, "Risk and regulation of emerging price volatility of non-staple agricultural commodity in China," *African Journal of Agricultural Research*, vol. 6, no. 5, pp. 1251–1256, 2011.

[6] C. S. Zhang, Z. H. Liu, and Y. Luo, "Goods financialization and inflation in China," *Economic Research Journal*, vol. 14, pp. 140–154, 2014.

[7] C. L. Gilbert, "How to understand high food prices," *Journal of Agricultural Economics*, vol. 61, no. 2, pp. 398–425, 2010.

[8] P. Went, B. Jirasakuldech, and R. Emekter, "Rational speculative bubbles and commodities markets: application of the duration dependence test," *Applied Financial Economics*, vol. 22, no. 7, pp. 581–596, 2012.

[9] P. Adämmer and M. T. Bohl, "Speculative bubbles in agricultural prices," *The Quarterly Review of Economics and Finance*, vol. 55, pp. 67–76, 2015.

[10] C. Gouel, "Agricultural price instability: a survey of competing explanations and remedies," *Journal of Economic Surveys*, vol. 26, no. 1, pp. 129–156, 2012.

[11] B. F. Massell, "Price stabilization and welfare," *Quarterly Journal of Economics*, vol. 83, no. 2, pp. 284–298, 1969.

[12] C. L. Gilbert, "International agreements to manage food price volatility," *Global Food Security*, vol. 1, no. 2, pp. 134–142, 2012.

[13] B. D. Wright, "Storage and price stabilization," in *Handbook of Agricultural Economics*, Chapter 14, B. L. Gardner and G. C. Rausser, Eds., vol. 1B, North Holland, Chapter 14, , pp. 817–861, 2001.

[14] X. Z. He and F. H. Westerhoff, "Commodity markets, price limiters and speculative price dynamics," *Journal of Economic Dynamics and Control*, vol. 29, no. 9, pp. 1577–1596, 2005.

[15] F. Westerhoff and C. Wieland, "A behavioral cobweb-like commodity market model with heterogeneous speculators," *Economic Modelling*, vol. 27, no. 5, pp. 1136–1143, 2010.

[16] H. Fernandez-Mena, B. Gaudou, S. Pellerin, G. K. MacDonald, and T. Nesme, "Flows in Agro-food Networks (FAN): an agent-based model to simulate local agricultural material flows," *Agricultural Systems*, vol. 180, Article ID 102718, 2020.

[17] L. Tesfatsion and K. Judd, Eds., *Handbook of Computational Economics: Agent-Based Computational Economics*, North Holland, Vol. 2, , Amsterdam, 2006.

[18] C. Hommes and B. LeBaron, Eds., *Handbook of Computational Economics: Heterogeneous Agent Modeling*, North Holland, Vol. 4, , Amsterdam, 2018.

[19] C. H. Hommes, "On the consistency of backward-looking expectations: the case of the cobweb," *Journal of Economic Behavior & Organization*, vol. 33, no. 3-4, pp. 333–362, 1998.

[20] C. H. Hommes, "Dynamics of the cobweb model with adaptive expectations and nonlinear supply and demand," *Journal of Economic Behavior & Organization*, vol. 24, no. 3, pp. 315–335, 1994.

[21] W. A. Brock and C. H. Hommes, "Heterogeneous beliefs and routes to chaos in a simple asset pricing model," *Journal of Economic Dynamics and Control*, vol. 22, no. 8-9, pp. 1235–1274, 1998.

[22] S. H. Strogatz, *Nonlinear Dynamics and Chaos*, CRC Press, Boca Raton, 2nd ed edition, 2019.

[23] L. P. Hansen and J. J. Heckman, "The empirical foundations of calibration," *The Journal of Economic Perspectives*, vol. 10, no. 1, pp. 87–104, 1996.

[24] F. E. Kydland and E. C. Prescott, "The computational experiment: an econometric tool," *The Journal of Economic Perspectives*, vol. 10, no. 1, pp. 69–85, 1996.

[25] S. H. Chen, C. L. Chang, and Y. R. Du, "Agent-based economic models and econometrics," *The Knowledge Engineering Review*, vol. 27, no. 2, pp. 187–219, 2012.

[26] Z. X. Chen and T. Lux, "Estimation of sentiment effects in financial markets: a simulated method of moments approach," *Computational Economics*, vol. 52, no. 3, pp. 711–744, 2018.

[27] R. Franke and F. Westerhoff, "Structural stochastic volatility in asset pricing dynamics: estimation and model contest," *Journal of Economic Dynamics and Control*, vol. 36, no. 8, pp. 1193–1211, 2012.

[28] D. Duffie and K. J. Singleton, "Simulated moments estimation of Markov models of asset prices," *Econometrica*, vol. 61, no. 4, pp. 929–952, 1993.

[29] J. Kukacka and L. Kristoufek, "Does parameterization affect the complexity of agent-based models?" *Journal of Economic Behavior & Organization*, vol. 192, pp. 324–356, 2021.

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Research Article

Developing Machine Learning Techniques to Investigate the Impact of Air Quality Indices on Tadawul Exchange Index

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The air quality index (AQI) can be described using different pollutant indices. Many investigators study the effect of stock prices and air quality in the field to show if there is a relationship between changing the stock market and the concentration of various pollutants. This study aims to find a relationship between Saudi Tadawul All Share Index (TASI) and multiple pollutants, including particulate matter (PM10), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and AQI. Based on tree models, the relationship is created using linear regression and two prediction models, Chi-square Automatic Interaction Detection (CHAID), and CR-Tree. In order to achieve the target of this research, the TASI dataset relates to six pollutants using time; afterward, the new dataset is divided into three parts—test, validate, and train—after eliminating the outlier data. In order to test the performance of two prediction models, R^2 and various error functions are used. The linear regression model results found that PM10, NO_2, CO, month, day, and year are significant, whereas O_3, SO_2, and AQI indices are insignificant. The test dataset showed that R^2 scores are 0.995 and 0.986 for CR-Tree and CHAID, respectively, with RMSE values of 387 and 227 for CR-Tree and CHAID, respectively. The prediction models showed that the CHAID model performed better than CR-Tree because it used only three indices, namely, PM10, AQI, and O_3, with year and month. The results indicated an effect between changing TASI and the three pollutants, PM10, AQI, and O_3.

1. Introduction

Climate change is an emergency beyond national borders; it is a worldwide situation where only collaboration between countries can solve it. In Paris, held in December 2015, the Paris climate agreement or COP21, started on 4 November 2016, with 195 countries signing it, and 190 approved it as of January 2021, as mentioned by the United Nations Framework Convention on Climate Change (UNFCCC). This agreement provides a robust pathway leading the global effort to achieve sustainable development goals and shift toward a net-zero emissions world. The primary purpose of this agreement includes promises from all countries to reduce their emissions and work together to adapt to the impacts of climate change. This agreement aims to limit global warming by minimizing greenhouse gas emissions to below 2°C, preferably to 1.5°C, compared to the temperature benchmark set before the beginning of the Industrial Revolution. Besides, the agreement built a structural plan to achieve a balance between atmospheric inputs of greenhouse gases by emission sources and removal into sinks after 2050. The Paris Agreement works on a 5-year cycle of increasingly ambitious climate action carried out by countries. Accordingly, countries in 2020 submitted their plans for climate action, known as nationally determined contributions. Furthermore, this agreement provides an outline for financial, technical, and capacity-building support to those countries that need it. Although the Paris Agreement declared that no new funding targets are required, it is preferable to see developed countries providing funding to help

developing countries. This funding mainly supports climate change mitigation and adaptation to climate impacts in less developed countries. This developed–developing support should walk on two parallel sides. On one side, the developed countries support the developing countries through grants, equipment, and technical expertise. On the other side, the less developed countries must enhance their economies and decrease poverty, resulting in solid and direct drops in greenhouse gas emissions.

Saudi Arabia, the world's leading fossil fuel exporter and the world's tenth-largest emitter of carbon dioxide (CO_2), showed an improvement in its pledge to climate action within its borders. By October 2021, the kingdom promised to cut its carbon emissions to net zero by 2060, which means not adding greenhouse gas emissions to the atmosphere. This announcement and many other actions end with upgrading its Climate Action Tracker (CAT) rating from "critically insufficient" to "highly insufficient." Although the Saudi economy depends heavily on oil production and its revenues, the Saudi government endorsed the Circular Carbon Economy (CCE) approach to managing emissions, mitigating climate challenge effects, and making energy systems cleaner and more sustainable. Moreover, the kingdom remains committed to the circular economy's four Rs (i.e., reduce, reuse, recycle, and renew). Saudi Arabia's national emissions have recently decreased after peaking in 2015 due to a decrease in oil consumption in the electricity sector, the COVID-19 impact on the economy, and the pandemic-related global decline in oil demand.

Furthermore, spokespersons of Saudi Arabia announced that the kingdom would achieve the net zero emissions target without affecting the "stability of global energy markets" through many actions. The kingdom aims to use renewable energy to generate 50% of electricity by 2030, as mentioned on the climate change news website. Moreover, Saudi Arabia has announced its aim of planting 450 million trees by 2030, the same as rehabilitating 200 million hectares of degraded land, with collaborative efforts to plant 50 billion trees in the Middle East, as CAT. Finally, the country would use carbon capture—a technology that extracts CO_2 from the air—to help it meet the goal. Several researchers explored the Saudi economy and exchange from different aspects [1, 2].

The air quality index (AQI) measures gas emissions in any country. AQI reports daily air quality and is like the weather; it can change daily or even from hour to hour. It tells to what extent the air is cleaned or polluted and what associated health effects might be a concern for people. The AQI focuses on health effects people may experience within a few hours or days after breathing polluted air. United States Environment Protection Agency (EPA) calculates the AQI for five major air pollutants regulated by the Clean Air Act: ground-level ozone, particle pollution [(particulate matter (PM10)], carbon monoxide (CO), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2). EPA has established national air quality standards for these pollutants to protect public health. Ground-level ozone and airborne particles are the two pollutants that pose the greatest threat to human health in this country. AQI is an index with a scale from 0 to 500. The higher the AQI value, the greater the level of air pollution and the greater the health concern. An AQI value of 50 represents good air quality with little or no potential to affect public health compared to an AQI value of over 300, which means air quality is so unsafe that everyone may have severe effects on their health, as explained on the airnow.gov website. Several scholars focused on investigating the effect of AQI levels on different countries' sectors and financial market indices. In this study, the authors are interested in filling the gap by examining the impact of Saudi AQI on the Saudi stock exchange index, Tadawul All Share Index (TASI).

Based on previous works, the effect of air quality indices on the stock market index is rarely studied by researchers, especially in Saudi Arabia. The studies used various linear and nonlinear models to understand the relationship between the independent variables (air quality indices and date variables) and dependent variables (TASI) without finding the most suitable model. Unfortunately, a few studies have suggested using various variables as an indicator to describe the effect of air pollutants on stock indices. This study presents multiple linear and nonlinear analyses to draw a relationship between independent and dependent variables. Our contribution to this work can be described as follows:

(1) The visualization test and linear regression model are used to show the capability of the linear model in finding a relationship between independent and dependent (TASI) variables

(2) Decision Tree models are used by selecting the two tree models, CR-Tree and Chi-square Automatic Interaction Detection (CHAID), to draw a nonlinear relationship between independent and dependent variables

(3) The prediction model is used to find the most effective pollutants associated with the TASI variable

This study comprises seven sections. Section 2 presents the literature review. Section 3 explains the methodology. Section 4 discusses the analysis. Section 5 describes the conclusions, and Section 6 provides the theoretical and practical implications.

2. Literature Review

This section presents the most related research that links to the environment and AQI, on the one hand, and the Stock Markets Return on the other hand.

2.1. The Environment Pillar Score and Financial Markets Return and Volatility. Many scholars were interested in studying the effect of the environment pillar as one of the sustainability pillars on stock market indices' return and volatility. The findings of Yoo et al. [3] indicate that the environment score significantly positively affects the stock market index, especially for the nonenergy sector. This result contradicts Merckoll and Kvarberg's [4] study, which investigated the effect of the environment pillar score on stock price volatility in Nordic countries from 2010 to 2019. Their

results showed a significant negative effect of the environment pillar score on stock price volatility. Besides, Hoepner et al. [5] presented significant adverse effects of a high environment pillar score on the downside risk. Lastly, Eratalay and Angel's [6] study concluded with an insignificant effect of the environment pillar score on the volatility of index return on the sample used.

Nevertheless, other researchers concentrated on other financial indicators, such as the effect of environment pillar score on financial performance and the efficiency of different financial institutes. Furthermore, Alam et al.'s [7] study investigated the effect of the environment pillar score on the efficiency of the Saudi banks and the other three Gulf Cooperation Council (GCC) countries. The outcomes of this study showed a positive *E* score effect on efficiency. Buallay et al. [8] examined the impact of the environment pillar score on Islamic banks' financial performance and found a positive effect of the environment pillar score on banks' performance. Lastly, Yang et al. [9] examined the relationship between financial instability, economic growth, energy consumption, trade openness, urban population, and CO_2 emissions. The findings showed a significant negative impact of financial instability on CO_2 emissions, whereas the increases in economic growth, energy consumption, and urban population are dangerous to the environment.

2.2. Effect of AQI on the Financial Markets. As mentioned before, AQI measures gas emissions in any country. AQI is calculated by considering different air pollutants, namely, SO_2, O_3, nitrogen oxides (NOx), CO_2, PM2.5, and PM10. When the concentration levels of these pollutants in the air increase, they become harmful to all living things around the environment, people, and animals [10, 11]. Many researchers were interested in studying the AQI and the ability of different prediction models to forecast the index using various machine learning models [12–20].

Many researchers have studied the effect of AQI during the COVID-19 period and investigated the positive effect of this pandemic on the worldwide environment, global warming, and gas emissions, as mentioned in Li [21]. Furthermore, Kar et al. [22] indicated that Indian indices had recovered during the pandemic. However, a few scholars studied the relationship between air pollution and the stock market index, as Cunha et al. [23] provided insight into the financial performance of a stock portfolio consisting of carbon-efficient Brazilian companies from 2010 to 2019 through different portfolio metrics. The results indicated that investing in carbon-efficient companies in Brazil contributed positively to the portfolio's performance.

El Ouadghiri et al. [24] studied the effect of public interest in pollution and climate change on weekly returns on indices of sustainability stock in the United States from 2004 to 2018. The findings indicated a significant positive relationship between the public interest in environmental issues and returns on sustainability stock indices in the United States. Moreover, Liu et al. [25] investigated the relationship between investor attention, stock prices, and air pollution. The findings exhibited that air pollution will reduce the polluting companies' stock prices.

According to Ding et al. [26], the results showed a negative relationship between air pollution and company stock returns, as companies in higher air-pollution cities showed lower stock returns. This pollution effect on the return becomes bigger when local investors manage firms with fewer institutional owners and analysts. Jiang et al. [27] investigated the impact of weather and air quality on the equity returns of the Shenzhen Exchange. The findings showed that, based on data from 2005 to 2012, air pollution has significant negative effects on stock returns.

Wu and Guo [28] investigated the relationship between the AQI and the stock yield in key control cities from 2011 to 2016. The findings revealed that severe air pollution significantly negatively influences stock yield. Xu et al. [29] studied the effect of air pollution on stock returns by considering people's awareness of air pollution. The results found that collective awareness of air pollution significantly mediates between air pollution and stock returns. Nguyen and Pham [30] studied the relationship between air pollution and the efficiency of the financial market. The results showed that the stock market anomalies weakened after the severe pollution period.

Other researchers study other essential factors; for example, investors' psychology and political events affect the stock return besides the environment and air pollution. Guo et al. [31] investigated how investor mood and environmental pillars are linked. Their results showed that air pollution negatively and positively affects individual investors buying and selling tendencies. These effects are more remarkable for investors who live in heavily polluted cities and have low investment experience. Antoniuk and Leirvik [32] examined unexpected political events affecting climate-sensitive sectors. These sectors are clean energy, utilities, energy-intensive, fossil energy, and transport. The events either enhance climate change awareness or weaken climate change policy. The results showed that stock market investors quickly adapt to new information regarding climate change.

3. Research Methodology

The research methodology is built after developing different nonlinear prediction models based on neural networks, support vector machines (SVM), Quick Unbiased Efficient Statistical Tree (QUEST), Tree-AS, random forest, CHAID, linear regression, generalized linear regression, and CR-Tree models [33–36]. After extensive study of previous work in the field, the models are considered to extract the most important prediction models in developing stock market prediction models. For brevity, only the highest accurate models are considered to develop the methodology for this research. Initial screening showed that CHAID and CR-Tree are the most accurate models. Meanwhile, linear regression with a visualization test is used to understand the linearity between independent variables (air quality indices and date) and dependent variables (TASI). Finally, this section mainly focuses on data collection and analysis, and the prediction

models are designed using two tree models, including CR-Tree and CHAID.

3.1. Data Collection and Analysis. The datasets are collected from two sources to study the relationship between air quality and the Saudi market index (TASI). The stock market index is compiled from the Saudi exchange website and finance.yahoo.com, where air quality indices are collected from two sources: Saudi Arabia General Authority for Meteorology and Environmental Protection and World Air Quality Index Project. The study considered different stations in Riyad, and the six pollutant indices' average values were evaluated. The stations are Khalidiya, Rawabi, Gharbi, Al-Jazeera, and Almurooj. Moreover, only five pollutants indices are measured in Riyad stations, namely, PM10 ($\mu g/m^3$), CO ($\mu g/m^3$), SO_2 ($\mu g/m^3$), NO_2 ($\mu g/m^3$), and O_3 ($\mu g/m^3$), as well as the AQI, where other pollutants (i.e., PM2.5 and CO_2) are not measured at stations or the collected values are few. The AQI is calculated by finding the maximum value of the five pollutants in an area, as shown in the World Air Quality Index Project. The dataset covers three years, from 2019 and 2021. After collecting the air quality indices and the TASI dataset, the two datasets are combined based on the data with 427 samples. Afterward, the data are cleaned, and the outlier data are removed. The cleaned and nonoutlier dataset is used to develop linear and nonlinear regression models. The descriptive statistic of the cleaned dataset is shown in Table 1. The initial analysis showed that the number of valid cases for pollutants is around 300, where the ranges of pollutants indices are from 1 to 58. The data covered three years with different months and days. In order to analyze the TASI indices, the study used data with the air quality indices to understand the effect of pollutants on the TASI index.

3.2. Develop Prediction Models Based on CR-Tree and CHAID Model. A Pearson correlation analysis is used with a p-value to study the relationship between independent variables (air quality indices) and dependent variables (TASI index). In addition, a visualization test is used to show the relationship between each input variable and the TASI value. Afterward, the linear regression model is adopted upon entering the method. Two tests are used to check the multicollinearity problem, including the VIF and Durbin–Watson tests.

Decision tree models are used to develop a prediction model using data and pollutants. A decision tree is a machine learning model that aims to create a relationship between output and input variables. There are two types of decision trees based on the type of independent variable, namely, categorical and continuous variable decision tree, which considers categorical and continuous variables as the independent variable, respectively. Based on IBM documentation for the SPSS modeler, tree modeling nodes are divided into four types: CR Tree, CHAID, QUEST, and C5.0. Each tree model has its strength and weakness, as discussed in [37]. In order to create a decision tree model, the following assumption must be fit as follows:

Table 1: Descriptive statistics of the cleaned data.

	N	Minimum	Maximum	Mean	Std. deviation
PM10	293	4	58	27.45	10.42
O_3	295	3	52	22.28	10.87
NO_2	292	2	19	9.50	3.41
SO_2	287	1	6	2.23	0.98
CO	275	6	27	14.05	4.91
AQI	300	11	58	30	9.74
TASI	300	6,287	11,512	8,716	1,376
Month	300	1	12	7.31	3.256
Day	300	1	31	15.45	8.750
Year	300	2019	2021	2020.01	0.769

(1) The training dataset is considered a root

(2) The discretized process is applied for continuous variables

(3) Records are distributed recursively

(4) A statistical approach moves from a root node to an internal node

A Sum of Product (SOP) is used to build a decision tree model. Besides, one of the primary challenges in making the decision tree is identifying the independent variable that must be considered a root node for each level. In order to select that, various attributes are considered in the literature, such as entropy, information gain, Gini index, and Chi-square.

In this study, the tree models are used to develop a prediction model. As the tree models are simple to understand and require little data preparation compared to other models, the prediction cost equals the logarithmic of the number of trained data. The decision tree contains many models such as random trees, random forest, C5 tree, Quest tree, Tree-AS, CHAID, and C and R-Tree. In this study, the last two models are selected for many reasons. The CR Tree is considered robust in missing data and large numbers of independent variables; the generated model is straightforward interpretation. On the contrary, the CR tree can generate only binary trees. Therefore, to develop a more robust and accurate model, the CHAID model is used because it can cause nonbinary stress and accept both case weights and frequency variables. In order to build a prediction model, the collected clean dataset is analyzed to check the complexity of the selected data. The dataset is divided into three datasets: train, validate, and test. The data are divided randomly with 70%, 15%, and 15% of the data for training, validating, and testing, respectively, as discussed by Al-Rousan et al. [38], AL-Najjar [39], and AL-Najjar et al. [40]. The training dataset is used to build a prediction model. The developed models are used with validating datasets to improve the prediction rate of the developed models. Afterward, a test dataset is used to check the capability of developed models.

The selected models are evaluated using five metrics, namely, determination coefficient (R^2), error and mean absolute error (MAE), root mean square error (RMSE), mean square error (MSE), mean bias error (MBE), as shown in the following:

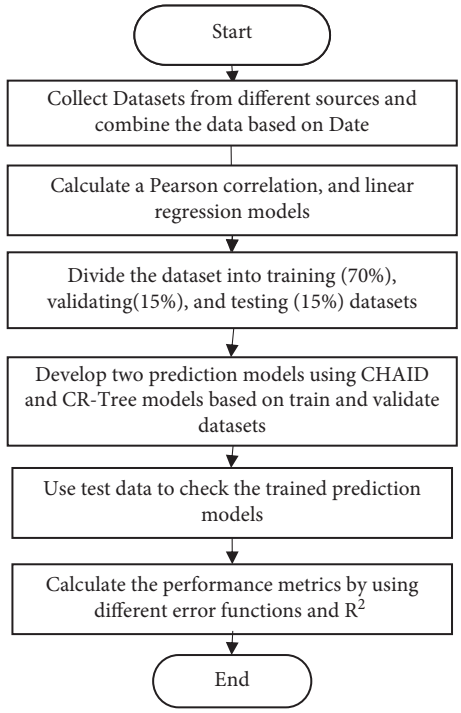

Figure 1: The methodology used to build models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \overline{y})^2},$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=0}^{N} (y_i - \hat{y}_i)^2},$$

$$MSE = \frac{1}{N} \sum_{i=0}^{N} (y_i - \hat{y}_i)^2, \quad (1)$$

$$MAE = \frac{1}{N} \sum_{i=0}^{N} |y_i - \hat{y}_i|,$$

$$MBE = \frac{1}{N} \sum_{i=0}^{N} y_i - \hat{y}_i.$$

where y_i, $\hat{y}_i$, and, $\overline{y}$ are TASI, the predicted TASI, and the mean of TASI, respectively. A flowchart in Figure 1 is considered to summarize all the used methodologies.

4. Result Analysis and Discussion

This section shows various analysis tests to understand the impact of air quality indices on TASI, including correlation analysis, visualization tests, linear regression, and prediction models. Therefore, this section is divided into three subsections: correlation analysis and visualization test, developed linear regression model, and CHAID and CR-Tree prediction models.

4.1. Correlation Analysis and Visualization Test. In order to understand the relationship between air quality indices and TASI, the relationship between air pollutants and TASI is drawn, as shown in Figure 2. The results showed no noticeable relationship between TASI and other pollutants for all the input data. The visual test showed that the lines gradually move with the air quality indices for TASI values from 7,000 to 8,000 and 10,500 to 11,800. Drawing a linear relationship between TASI and air pollutants alone is not possible. Therefore, the date is added to the analysis to support developing linear regression and prediction models.

Before building a linear regression model, a correlation analysis is used to check the possibility of finding a linear regression between independent variables (air quality indices and date) and dependent variables (TASI index). Table 2 shows that the TASI index is insignificantly correlated with PM10, O_3, NO_2, AQI, month, and day, where SO_2 and year are positively correlated with TASI with a correlation coefficient of 0.295 and 0.693, respectively. In addition, CO corrected significantly (correlation level = −0.327, $p < 0.05$) with TASI with an inverse relationship.

On the contrary, one of the crucial tests that must be considered while building a linear regression model is to check the multicollinearity problem; the results in Table 2 reveal that there is a multicollinearity problem, especially between AQI and other pollutants, which may cause unreal linear regression model between the studied variables.

4.2. Developed Linear Regression Model. Linear regression is created to evaluate a linear relationship between air pollutants and TASI, as shown in Tables 3–5. Date and six pollutants indices are used to develop a linear regression model. The results showed that R^2 and standard error are 0.735 and 746, respectively. Moreover, the analysis of variance (ANOVA) test is used to show how TASI changes according to the air quality indices and date level. The results in Table 4 show a significant effect of some pollutant indices and date variables on TASI movement at the $p < 0.05$ level for the three conditions [$F(43828747, 556966) = 79$, $p = 0.000$].

The coefficients of the linear regression are reported in Table 5. The results showed that PM10, NO_2 CO, month, day, and year are significant, whereas O_3, SO_2, and AQI indices are insignificant with TASI. This indicates that the model did not consider the last three indicators in building the model. The preliminary analysis showed which hands were essential to the model but did not show the most critical and most affected variables in the developed linear regression model. In order to check this, unstandardized and standardized coefficients are used. The results showed that the indices of the month, year, and CO had the highest weight on the linear regression model, and the month, year, and PM10 had the highest effect on the linear regression model.

In contrast, to test the multicollinearity problem of the linear regression model, the Durbin–Watson and VIF tests are adopted. The VIF test showed that all the variables did not exceed 10, which indicates that VIF traverses multicollinearity problems, as shown in Table 5. Unfortunately, the Durbin–Watson value is 0.323, meaning a positive multicollinearity problem in the model, as shown in Table 3.

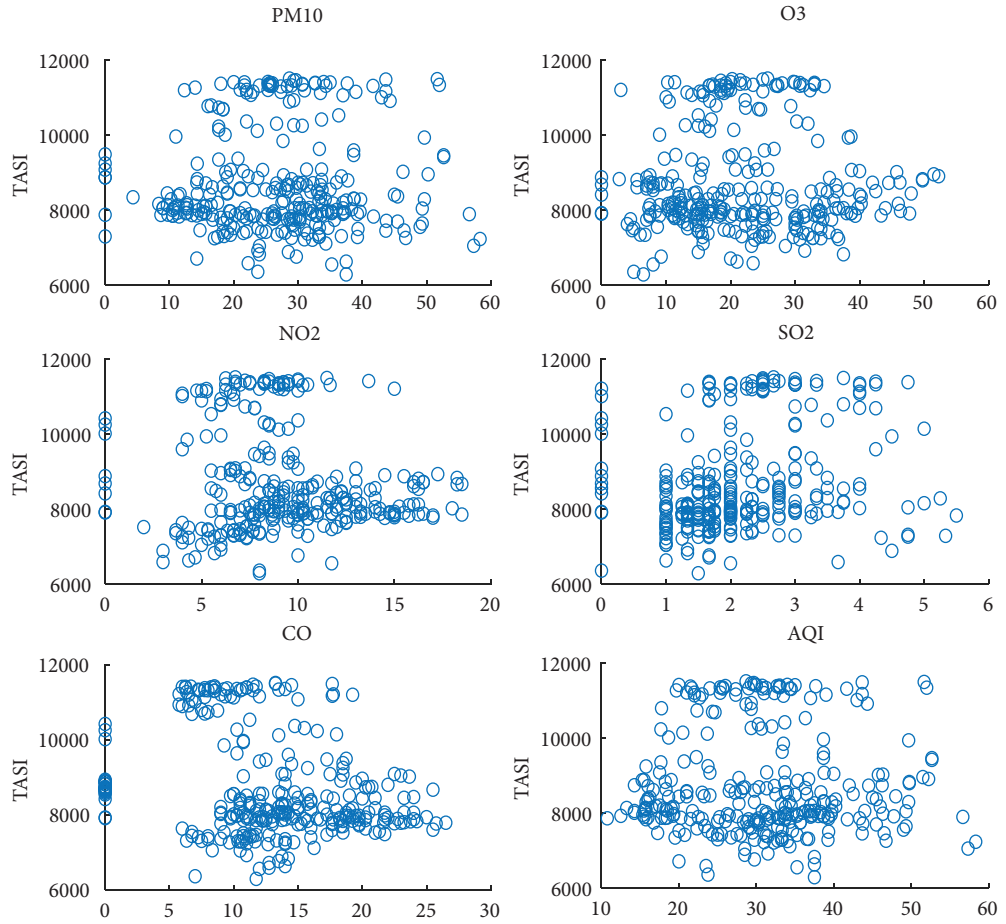

Figure 2: The relationship between the leading pollutant indices and the TASI index.

Table 2: Correlation analysis.

		PM10	O_3	NO_2	SO_2	CO	AQI	Month	Day	Year	TASI
PM10	Corr.	1.000	0.152**	−0.267**	0.163**	−0.176**	0.804**	0.026	0.172**	0.160**	0.043
	Sig.		0.010	0.000	0.006	0.004	0.000	0.660	0.003	0.006	0.466
O_3	Corr.	0.152**	1.000	−0.227**	0.199**	0.194**	0.563**	0.224**	0.005	−0.248**	0.003
	Sig.	0.010		0.000	0.001	0.001	0.000	0.000	0.933	0.000	0.962
NO_2	Corr.	−0.267**	−0.227**	1.000	−.066	0.335**	−0.267**	0.284**	−0.028	−0.320**	−0.113
	Sig.	0.000	0.000		0.265	0.000	0.000	0.000	0.633	0.000	0.053
SO_2	Corr.	0.163**	0.199**	−0.066	1.000	−0.125*	0.165**	0.088	0.048	0.266**	0.295**
	Sig.	0.006	0.001	0.265		0.041	0.005	0.135	0.417	0.000	0.000
CO	Corr.	−0.176**	0.194**	0.335**	−0.125*	1.000	0.002	0.054	−0.035	−0.585**	−0.327**
	Sig.	0.004	0.001	0.000	0.041		0.977	0.370	0.561	0.000	0.000
AQI	Corr.	0.804**	0.563**	−0.267**	0.165**	0.002	1.000	0.085	0.158**	−0.057	−0.013
	Sig.	0.000	0.000	0.000	0.005	0.977		0.140	0.006	0.325	0.823
Month	Corr.	0.026	0.224**	0.284**	0.088	0.054	0.085	1.000	−0.048	−0.422**	0.060
	Sig.	0.660	0.000	0.000	0.135	0.370	0.140		0.409	0.000	0.298
Day	Corr.	0.172**	0.005	−0.028	0.048	−0.035	0.158**	−0.048	1.000	0.027	0.039
	Sig.	0.003	0.933	0.633	0.417	0.561	0.006	0.409		0.639	0.501
Year	Corr.	0.160**	−0.248**	−0.320**	0.266**	−0.585**	−0.057	−0.422**	0.027	1.000	0.693**
	Sig.	0.006	0.000	0.000	0.000	0.000	0.325	0.000	0.639		0.000
TASI	Corr.	0.043	0.003	−0.113	0.295**	−0.327**	−0.013	0.060	0.039	0.693**	1.000
	Sig.	0.466	0.962	0.053	0.000	0.000	0.823	0.298	0.501	0.000	

**Significant at the 0.01 level (two-tailed). *Significant at the 0.05 level (two-tailed).

Table 3: Linear regression summary.

Model	R	R^2	Adjusted R^2	Std. error	Durbin–Watson
1	0.857[a]	0.735	0.726	746	0.323

[a]Predictors: (constant), year, day, AQI, SO_2, month, NO_2, O_3, CO, PM10.

Table 4: ANOVA test for the linear regression model.

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	394,458,723	9	43,828,747	79	0.000[b]
	Residual	142,026,398	255	556,966		
	Total	536,485,121	264			

b:this model is significant at $P<0.01$.

Table 5: Coefficients of the linear regression.

Model		Unstandardized Coefficients		Standardized coefficients			Collinearity Statistics	
		B	std. error	Beta	t	Sig.	tolerance	VIF
1	(Constant)	−4244019	189,007		−22.45	0.00		
	PM10	−30.87	9.62	−0.23	−3.21	0.00	0.20	4.96
	O_3	9.05	7.17	0.07	1.26	0.21	0.36	2.74
	NO_2	43.42	18.82	0.09	2.31	0.02	0.62	1.61
	SO_2	−62.05	52.78	−0.04	−1.18	0.24	0.79	1.27
	CO	68.20	12.57	0.24	5.42	0.00	0.55	1.81
	AQI	21.38	12.23	0.15	1.75	0.08	0.15	6.65
	Month	211.95	19.29	0.45	10.99	0.00	0.62	1.62
	Day	11.09	5.37	0.07	2.06	0.04	0.95	1.05
	Year	2103.86	93.49	1.13	22.50	0.00	0.41	2.43

Table 6: CHAID and CR-Tree prediction results analysis.

	CR-Tree			CHAID		
	Train	Test	Validate	Train	Test	Validate
R^2	0.995	0.972	0.962	0.979	0.986	0.994
MSE	20,240	104,592	149,478	79,746	51,581	21,717
MAE	103	228	255	182	166	112
MBE	0.000	−63.707	41.184	18.177	4.452	21.737
RMSE	142	323	387	282	227	147

Therefore, the linear regression model failed to develop a relationship between air pollutant indices with date variables and TASI values.

4.3. Developed CHAID and CR-Tree Prediction Models. In order to solve the problem in the linear regression model problem and build a system that can predict TASI values accurately and study the most affected pollutants from TASI changes, this section aims to develop two TASI predictions and tree models. Two tree models (i.e., CHAID and CR-Tree) and three datasets (including train, test, and validate) are used. The train results of CR-Tree are 0.995, 20,240, 103, 0.000, and 142, whereas, for the test, the results are 0.962, 149,478, 255, 41.184, and 387 for R^2, MSE, MAE, MBE, and RMSE, respectively, as shown in Table 6. Moreover, the CHAID model results of the training dataset are 0.979, 79,746, 182, 18, and 282, whereas, for the test dataset, the results are 0.986, 51,581, 166, 4, and 227 for R^2, MSE, MAE, MBE, and RMSE, respectively, as shown in Table 6. The results indicated that the CHAID model is more stable and accurate than the CR-Tree model as the prediction rate for testing is higher than the CR-Tree model and the error values are less for all cases.

A visual test is used with the collected data to support the claim of the collected results, as shown in Figures 3 and 4. Figure 3 shows the relationship between the collected data and the TASI values. Three lines are drawn: actual TASI values, CHAID predicted values, and CR-Tree predicted values. The results showed that CHAID and CR-Tree predictors move with TASI values, with CHAID having a more remarkable ability to track increases and decreases in the actual TASI values. In addition, Figure 4 shows the error for each sample using CHAID and CR-Tree predictors; the CHAID results were more accurate than the CR-Tree results.

Moreover, CR-Tree and CHAID used different variables to develop TASI prediction models, as shown in Figure 5. The CR-Tree model used eight variables, including month, day, NO_2, PM10, O_3, AQI, SO_2, and CO, whereas CHAID used only five variables: month, year,

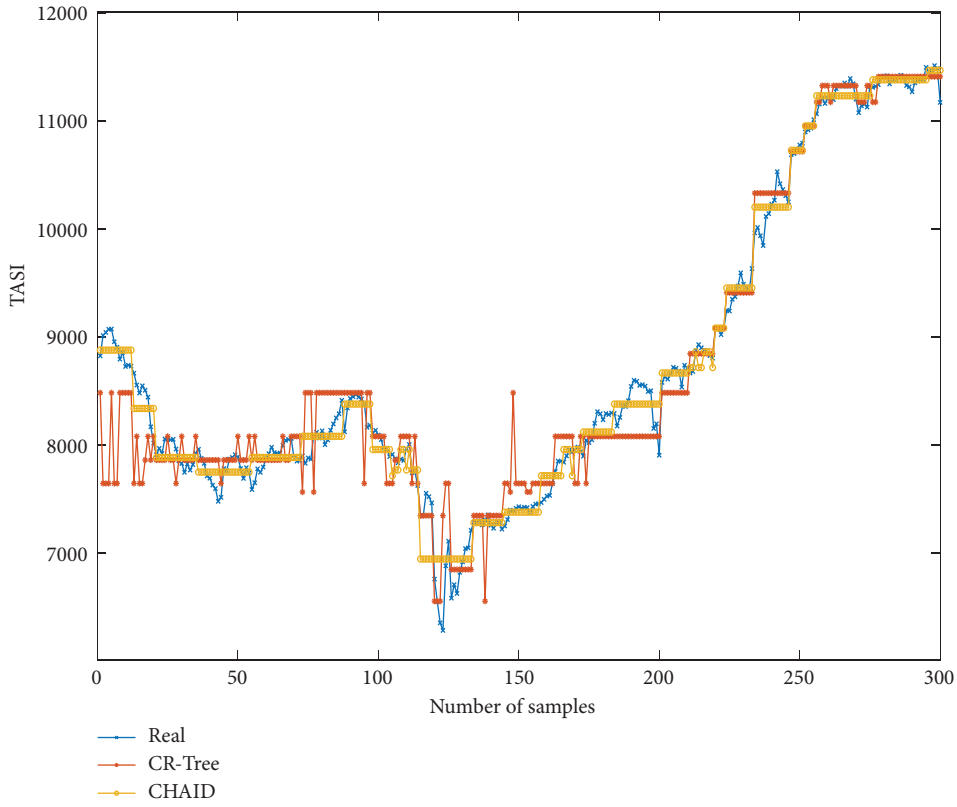

Figure 3: The relationship between all samples and the TASI value using real, CR-Tree, and CHAID models.

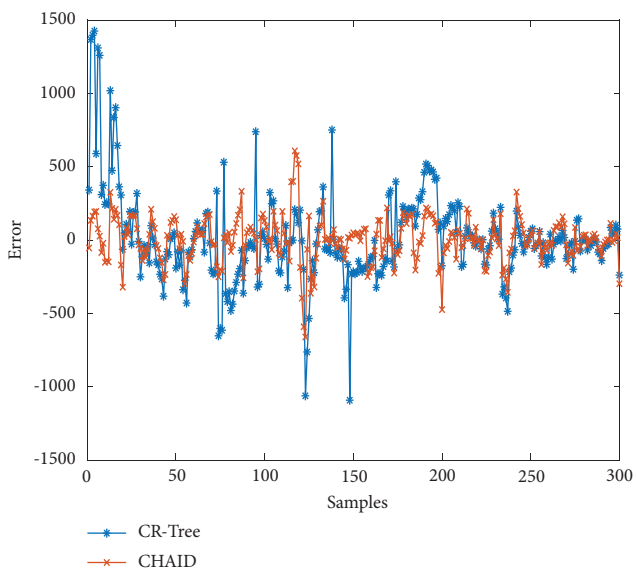

Figure 4: Train error function, testing, and validating samples using CR-Tree and CHAID.

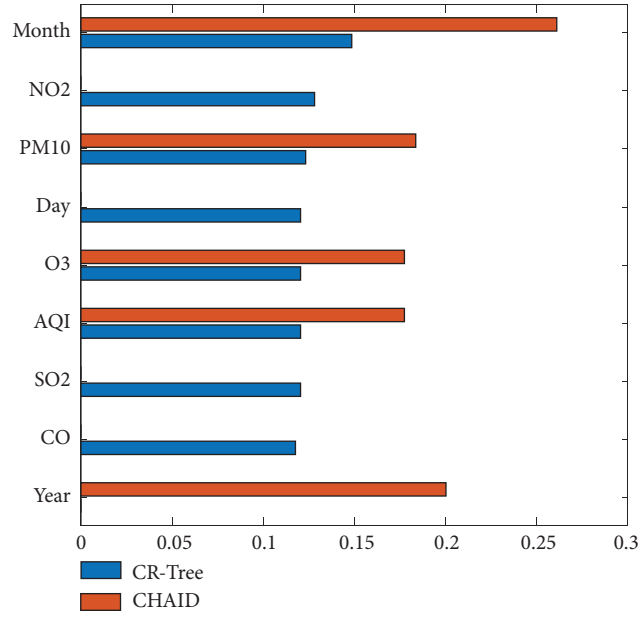

Figure 5: The importance variable for CHAID and CR-Tree models.

PM10, O_3, and AQI. CR-Tree showed that the top four important variables (arranged from most important to least important) are month, NO_2, PM10, and day, whereas the top four important variables in CHAID are month, year, PM10, O_3, and AQI. By combining the collected results and the linear regression analysis, the results found that the CHAID model is more realistic than CR-Tree, as a month, year, and three pollutants indices were included in the developed model.

Furthermore, to understand the complexity of the developed CR-Tree and CHAID prediction models, partial classification trees are explained in Figures 6 and 7, respectively. Tree's depths for CR-Tree and CHAID models are 5 and 3, respectively. CR-Tree model starts by merging 2020

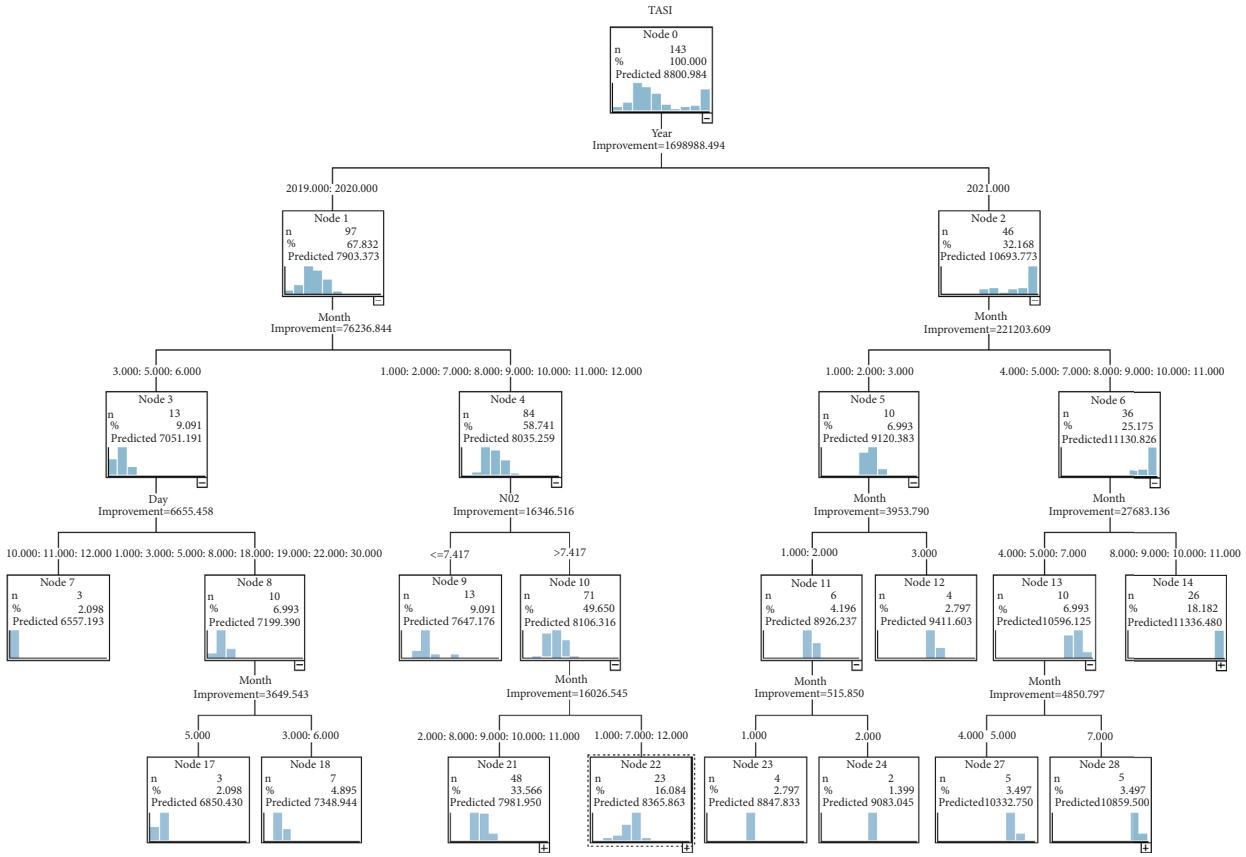

Figure 6: Partial classification tree for TASI CR-Tree predictor.

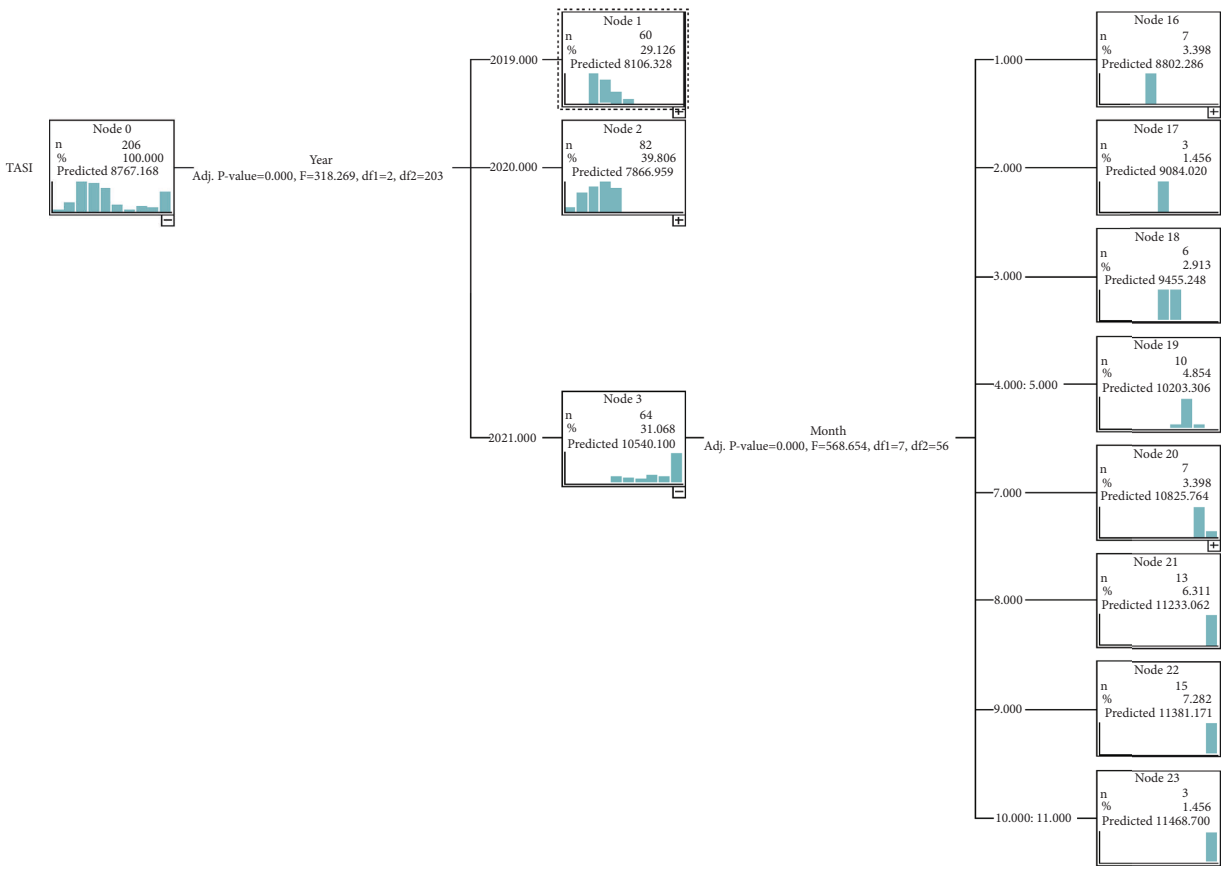

Figure 7: Partial classification tree for TASI CHAID predictor.

and 2019. Afterward, the month variable is used as the main variable for classification. The day, NO_2, and month are used for the second level, whereas the month and CO variables are used for the third and fourth levels, respectively. On the contrary, the CHAID model starts by dividing the data into three parts based on the year variable; then, the month is used to classify the data as the main parameter. Afterward, PM10, AQI, and O_3 are used as the last level for TASI classification.

There is no known research article for authors who predicted Tadawul All Share Index (TASI) using air quality indices as independent variables. Therefore, the researchers compared the best results with most research that predicted the stock market using neural network models described in [36] and [41]. Assous and Al-Najjar [36] reported that the neural network model is the best in stock market predictions. The R^2 and RMSE error values for TASI prediction are 0.96 and 194, respectively. In addition, Malibari et al. [41] predicted the TASI closing index with an accuracy of about 97% and low error values for different batches. The overall results showed that the CHAID model can predict stock markets using date and air quality indices.

To sum up, analytical analysis, visual test, and linear regression model with tree design showed that developing a prediction model using tree models is efficient and accurate in predicting the TASI values. The tests indicated that the CHAID model is correct, robust, stable, realistic, and less complicated than the CR-Tree model. The results revealed a strong relationship between TASI changes and three air quality indices, including AQI, PM10, and O_3.

5. Conclusion and Future Work

The research aims to study the relationship between air pollutant indices with the date and the TASI index (Saudi stock index) in the last three years. The investigation started by collecting air quality indices and TASI values; both datasets are combined based on date. The newly collected dataset is preprocessed to remove the outlier data. As a first step to understanding the relationship between independent variables (air pollutants and date) and dependent variables (TASI value), a linear regression model is used with a visualization test. The results showed a weak linear relationship between air quality indices with date and TASI. Therefore, nonlinear tree models are used to find the relationship between independent and dependent variables. The study used two tree models, including CHAID and CR-Tree. The train results of CR-Tree are 0.995, 20,240, 103, 0.000, and 142, whereas, for the test, the results are 0.962, 149,478, 255, 41.184, and 387 for R^2, MSE, MAE, MBE, and RMSE, respectively, where the CHAID model results of the training dataset are 0.979, 79,746, 182, 18, and 282, whereas, for the test dataset, the results are 0.986, 51581, 166, 4, and 227 for R^2, MSE, MAE, MBE, and RMSE, respectively. The results found that the CHAID model performed better than CR-Tree. The results indicated a nonlinear effect between TASI and three air quality indices, including AQI, PM10, and O_3. CHAID results showed that air quality indices increased the performance of the stock market prediction model, in contrast to [36] and [41], which showed that the neural network model is more accurate than other models in developing stock market prediction models. This gives strong evidence that the changing air quality indices can reflect changes in TASI values. Unfortunately, this will not provide complete evidence about the effect of pollutants' indices on TASI and the direction of the impact, as the decision tree models are nonlinear prediction models. Therefore, extra analysis is required to understand the direction and the important variables that can improve the performance of the prediction models. In future work, the authors aim to improve the prediction model using different machine learning models, including clustering and reinforcement learning. In addition, extra variables such as humidity and temperature are needed to understand their performance on the TASI variable [42].

6. Theoretical and Practical Implications

This study is necessary for academics, scholars, and investors in the field of stock market trading in Saudi Arabia. This study investigates the effect of air pollution with air quality indices on the stock market in the last three years. In order to achieve the target of this study, two tree models are used with different independent variables. Besides, the study only dealt with the general stock index in the Kingdom of Saudi Arabia, which is the Saudi Stock Exchange index (TASI).

Traffic and weather are the main reasons for changing stock trading in some countries. Different pollutants from cars and changing the weather are considered to study, including PM10, O_3, NO_2, SO_2, and CO. In this study, the authors proved that the stock market responds powerfully to the variations in air quality indices in Riyad (the capital of Saudi Arabia). In addition, the results show that climate changes in the atmosphere could cause indirect changes in the price of TASI values.

In addition, policymakers can use this research result to monitor the traffic of cars, power plants, industrial boilers, power generators, pollen, and other sources of O_3 and PM10 pollutants. Furthermore, the results may trigger the shareholders to find suitable dates for selling and buying their shares. Besides, more regulations must be considered on the traffic to decrease the pollutants in the air.

Finally, the societal benefit of the findings of this research can be summarized as follows: (1) the researchers demonstrated a strong influence of PM10, O_3, and AQI on stock market predictions, and this would give an initial indication that pollution could have an initial alarm on reducing or increasing stock trading. (2) Using a CHAID with the date and air pollutants to predict the stock market can improve the accuracy of the stock prediction. Therefore, new shareholders and investors can use this feature to buy and sell shares of stock.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request by Dr. Dania Al-Najjar.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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References

[1] D. Al-Najjar and H. F. Assous, "Key determinants of deposits volume using CAMEL rating system: the case of Saudi banks," *PLoS One*, vol. 16, no. 12, Article ID e0261184, 2021.

[2] H. F. Assous, N. Al-Rousan, D. Al-Najjar, and H. Al-Najjar, "Can international market indices estimate TASI's movements? The ARIMA model," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, no. 2, pp. 27–18, 2020.

[3] S. Yoo, A. R. Keeley, and S. Managi, "Does sustainability activities performance matter during financial crises? Investigating the case of COVID-19," *Energy Policy*, vol. 155, Article ID 112330, 2021.

[4] H. Merckoll and O. Kvarberg, "Har ESG-score en Effekt på Aksjeprisvolatilitet i det Nordiske Markedet? En Empirisk Studie," Master's thesis, University of stavanger, Norway, 2021.

[5] A. G. F. Hoepner, I. Oikonomou, Z. Sautner, L. T. Starks, and X. Zhou, "ESG shareholder engagement and downside risk," 2019, https://ssrn.com/abstract=2874252.

[6] M. H. Eratalay and A. P. Cortés Ángel, "The impact of ESG ratings on the systemic risk of European blue-chip firms," *Journal of Risk and Financial Management*, vol. 15, no. 4, p. 153, 2022.

[7] A. W. Alam, H. Banna, and M. K. Hassan, "ESG activities and bank efficiency: are Islamic banks better?" Available at SSRN 4030145, 2021.

[8] A. Buallay, "Is sustainability reporting (ESG) associated with performance? Evidence from the European banking sector," *Management of Environmental Quality: An International Journal*, vol. 30, no. 1, pp. 98–115, 2019.

[9] B. Yang, M. Ali, M. R. Nazir, W. Ullah, and M. Qayyum, "Financial instability and CO2 emissions: cross-country evidence," *Air Quality, Atmosphere & Health*, vol. 13, no. 4, pp. 459–468, 2020.

[10] L. N. Araujo, J. T. Belotti, T. A. Alves, Y. d. S. Tadano, and H. Siqueira, "Ensemble method based on Artificial Neural Networks to estimate air pollution health risks," *Environmental Modelling & Software*, vol. 123, Article ID 104567, 2020.

[11] C. Shi, I. C. Nduka, Y. Yang et al., "Characteristics and meteorological mechanisms of transboundary air pollution in a persistent heavy PM2. 5 pollution episode in Central-East China," *Atmospheric Environment*, vol. 223, Article ID 117239, 2020.

[12] S. Hansun, A. Wicaksana, and M. B. Kristanda, "Prediction of Jakarta City air quality index: modified double exponential smoothing approaches," *Int J Innov Comput Inf Control*, vol. 17, no. 4, pp. 1363–1371, 2021.

[13] L. Hota, P. K. Dash, K. S. Sahoo, and A. H. Gandomi, "Air quality index analysis of Indian cities during COVID-19 using machine learning models: a comparative study," in *Proceedings of the 2021 8th International Conference on Soft Computing & Machine Intelligence (ISCMI)*, pp. 27–31, IEEE, Cario, Egypt, November 2021.

[14] Y. Mo, Q. Li, H. Karimian et al., "A novel framework for daily forecasting of ozone mass concentrations based on cycle reservoir with regular jumps neural networks," *Atmospheric Environment*, vol. 220, Article ID 117072, 2020.

[15] M. Yu, X. Cai, Y. Song, and X. Wang, "A fast-forecasting method for PM2. 5 concentrations based on footprint modeling and emission optimization," *Atmospheric Environment*, vol. 219, Article ID 117013, 2019.

[16] Z. Wang, L. Chen, Z. Ding, and H. Chen, "An enhanced interval PM2. 5 concentration forecasting model based on BEMD and MLPI with influencing factors," *Atmospheric Environment*, vol. 223, Article ID 117200, 2019.

[17] H. Liu and C. Chen, "Prediction of outdoor PM2. 5 concentrations based on a three-stage hybrid neural network model," *Atmospheric Pollution Research*, vol. 11, no. 3, pp. 469–481, 2020.

[18] H. d. He and Wz Lu, "Comparison of three prediction strategies within PM2. 5 and PM10 monitoring networks," *Atmospheric Pollution Research*, vol. 11, no. 3, pp. 590–597, 2020.

[19] S. Zhu, X. Qiu, Y. Yin et al., "Two-step-hybrid model based on data pre-processing and intelligent optimization algorithms (CS and GWO) for NO2 and SO2 forecasting," *Atmospheric Pollution Research*, vol. 10, no. 4, pp. 1326–1335, 2019.

[20] A. Alimissis, K. Philippopoulos, C. G. Tzanis, and D. Deligiorgi, "Spatial estimation of urban air pollution with the use of artificial neural network models," *Atmospheric Environment*, vol. 191, pp. 205–213, 2018.

[21] X. Li, "On the multifractal analysis of air quality index time series before and during COVID-19 partial lockdown: a case study of Shanghai, China," *Physica A: Statistical Mechanics and its Applications*, vol. 565, Article ID 125551, 2021.

[22] S. Kar, I. Ghosh, S. Show et al., "Impact of coronavirus (COVID-19) outbreak on society, air quality, and economy in India: a study of three "P" s of sustainability in India," *Sustainability*, vol. 13, no. 5, p. 2873, 2021.

[23] F. A. F. d. S. Cunha, E. Meira, R. J. Orsato, M. C. Klotzle, and A. F. Lucena, "Do low-carbon investments in emerging economies pay off? Evidence from the Brazilian stock market," *International Review of Financial Analysis*, vol. 74, Article ID 101700, 2021.

[24] I. El Ouadghiri, K. Guesmi, J. Peillex, and A. Ziegler, "Public attention to environmental issues and stock market returns," *Ecological Economics*, vol. 180, Article ID 106836, 2021.

[25] F. Liu, Y. Kang, K. Guo, and X. Sun, "The relationship between air pollution, investor attention and stock prices: evidence from new energy and polluting sectors," *Energy Policy*, vol. 156, Article ID 112430, 2021.

[26] X. Ding, M. Guo, and T. Yang, "Air pollution, local bias, and stock returns," *Finance Research Letters*, vol. 39, Article ID 101576, 2021.

[27] Z. Jiang, R. Gupta, S. Subramaniam, and S. M. Yoon, "The effect of air quality and weather on the Chinese stock: evidence from shenzhen stock exchange," *Sustainability*, vol. 13, no. 5, p. 2931, 2021.

[28] X. Wu, S. Chen, J. Guo, and G. Gao, "Effect of air pollution on the stock yield of heavy pollution enterprises in China's key control cities," *Journal of Cleaner Production*, vol. 170, pp. 399–406, 2018.

[29] M. Xu, Y. Wang, and Y. Tu, "Uncovering the invisible effect of air pollution on stock returns: a moderation and mediation analysis," *Finance Research Letters*, vol. 39, Article ID 101646, 2021.
[30] H. T. Nguyen and M. H. Pham, "Air pollution and behavioral biases: evidence from stock market anomalies," *Journal of Behavioral and Experimental Finance*, vol. 29, Article ID 100441, 2021.
[31] M. Guo, M. Wei, and L. Huang, "Does air pollution influence investor trading behavior? Evidence from China," *Emerging Markets Review*, vol. 50, Article ID 100822, 2022.
[32] Y. Antoniuk and T. Leirvik, "Climate change events and stock market returns," *Journal of Sustainable Finance & Investment*, vol. 26, 2021.
[33] D. Al-Najjar, "The Co-movement between international and emerging stock markets using ANN and stepwise models: evidence from selected indices," *Complexity*, vol. 2022, Article ID 7103553, 14 pages, 2022a.
[34] H. F. Assous, "Prediction of banks efficiency using feature selection method: comparison between selected machine learning models," *Complexity*, vol. 2022, Article ID 3374489, 2022.
[35] H. Al-Najjar, N. Al-Rousan, D. Al-Najjar, H. F. Assous, and D. Al-Najjar, "Impact of COVID-19 pandemic virus on G8 countries' financial indices based on artificial neural network," *Journal of Chinese Economics and Foreign Trade Studies*, vol. 14, no. 1, pp. 89–103, 2021.
[36] H. F. Assous and D. Al-Najjar, "Consequences of COVID-19 on banking sector index: artificial neural network model," *International Journal of Financial Studies*, vol. 9, no. 4, p. 67, 2021.
[37] A. Melsayad and H. A Elsalamony, "Diagnosis of breast cancer using decision tree models and SVM," *International Journal of Computer Application*, vol. 83, no. 5, pp. 19–29, 2013.
[38] N. Al-Rousan, N. A. Mat Isa, M. K. Mat Desa, and H. Al-Najjar, "Integration of logistic regression and multilayer perceptron for intelligent single and dual axis solar tracking systems," *International Journal of Intelligent Systems*, vol. 36, no. 10, pp. 5605–5669, 2021.
[39] D. Al-Najjar, "Impact of the twin pandemics: COVID-19 and oil crash on Saudi exchange index," *PLoS One*, vol. 17, no. 5, Article ID e0268733, 2022b.
[40] D. Al-Najjar, H. F. Assous, H. Al-Najjar, and N. Al-Rousan, "Ramadan effect and indices movement estimation: a case study from eight Arab countries," *Journal of Islamic Marketing*, vol. 7, 2022.
[41] N. Malibari, I. Katib, and R. Mehmood, "Predicting stock closing prices in emerging markets with transformer neural networks: the Saudi stock exchange case," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 12, 2021.
[42] H. Al-Najjar and N. Al-Rousan, "A classifier prediction model to predict the status of Coronavirus CoVID-19 patients in South Korea," *European Review for Medical and Pharmacological Sciences*, vol. 24, 2020.

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Research Article

The Behavior and Impact of Heterogeneous Investors in China's Stock Index Futures Market: An Agent-Based Model on Cross-Market Trades

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Since the period of unusual volatility in China's A-share market in 2015, there has been an ongoing discussion about the role of stock index futures in the A-share market. There is no unified consensus among academics and industry insiders on whether stock index futures affect spot market volatility. Using agent-based modeling, we construct a theoretical model of the order book of the stock index futures market to assess the microbehavior of speculators, arbitrageurs, and hedgers in this market. We then calibrate the link between the futures and spot models to explore the respective influences of heterogeneous investors in the two markets. We find that speculators, arbitrageurs, and hedgers all play different roles and have varying effects on the two markets. While speculators serve as the foundation for other investors to participate in trading activities, both arbitrageurs and hedgers affect the spot market by significantly reducing volatility, enhancing price efficiency, and playing a positive role in the operation of this market. We develop our model from the perspective of investor behavior and explain why the stock index futures market can reduce spot market volatility. In addition, our conclusion may help regulators understand the roles played by different types of investors in the Chinese stock index futures market.

1. Introduction

From June to August 2015, the Chinese stock market experienced a period of rare and unusual volatility. During this period, public opinion tended to cite stock index futures as the culprit for this unusual spot volatility, and there were even calls for the suspension of stock index futures trading. In addition, the China Financial Futures Exchange made five adjustments (the five adjustments were made on August 26, 27, 28, and 31 and September 7, 2015. The last adjustment resulted in the following: the trading margin for nonhedging positions is 40% of the contract value, the trading margin for hedging positions is 20% of the contract value, the intraday transaction fee for opening and closing positions is 23% per 10,000, and the single product opening and trading volume of more than 10 lots in a single day is considered abnormal behavior of "large intraday opening and trading volume") to trading margin, intraday position opening volume, and same day closing costs in the stock index futures market in a short period. Since the occurrence of this unusual volatility, researchers have continued to explore the performance of stock index futures and their role in this rare event [1–4], and similar conclusions have been reached in studies by scholars such as Huang et al. [5], Wang et al. [6], Mou and Yuan [7], and Jian et al. [8].

A 2015 report issued by the National Institute of Finance at Tsinghua University, titled "Improving Institutional Design and Enhancing Market Confidence—Building a Capital Market for Long-Term Healthy and Stable Development," cites the reutilization of the investor structure, a

short-sighted and weakened value investment philosophy, and a significant herd effect in the Chinese spot market as the underlying causes of this abnormal volatility [9]. The report also concludes that investors in the stock index futures market played an active role in causing this volatility, as the risk management function of stock index futures was insufficient during the period. At the same time, the report attests to the positive effects of diverting selling pressure away from spot markets.

In response to the report's findings, a research question has arisen. The Chinese market is dominated by retail investors with heterogeneous beliefs and driven by the adaptive asset allocation strategy of "chasing ups and downs" what kind of cross-market impact will different types of investors in the stock index futures market have on the spot market? Several researchers conducted studies on the impact of the stock index futures market on spot market volatility in the Chinese market. For example, Wang et al. [10] analyzed the basic characteristics of market yield volatility based on the five-minute trading data of the Chinese CSI 300 stock index futures. Cao et al. [11] found strong evidence that the measure of Chinese investor sentiment drives abnormal fluctuations on the basis of China's stock index futures. However, relevant studies fall into three broad categories due to differences in research methods and data selection intervals: stock index futures reduce spot market volatility [12–15], stock index futures increase volatility in the spot market [16, 17], and stock index futures have no significant impact on the volatility of the spot market [17, 18]. Overall, the numerous studies on the topic do not form a consistent view.

Modeling of similar markets such as stock index futures falls into two main categories: one uses statistical empirical models to predict the future based on large amounts of historical data, but the disadvantage of such models is that they become ineffective when the market is hit by a catastrophic event in the short term; the other type of model forms what appears to be a perfect economic world, but none of its assumptions are true. Financial crises and other "black swan" events have shaken the understanding of conventional models. Agent-based modeling is an attempt to model the complexity of the financial system and the microparticipant behavior of investors. According to Zhang et al. [18], the approach is to view the financial market as a system comprised of multiple adaptive heterogeneous subjects, to use intelligent information technology to micromodel the catering learning behavior of these subjects and their interactions under a given market structure, thereby forming a simulated financial market, and to explain the dynamic characteristics of the market and its causes by simulating the market and conducting microscopic experiments. NASDAQ was the first organization to use agent-based modeling as a method for financial regulation. Darley et al. [19] developed an agent-based model to investigate the mechanism design problem of adjusting the minimum quotation unit from 1/8 to 1/16, which provides decision support for NASDAQ market policymaking. In recent years, several agent-based modeling studies on institutional design, such as Li et al. [20], Wei et al. [21], and Zhang et al. [22], have emerged based on the specific context of the trading system in the Chinese market. Accordingly, agent-based modeling is widely used to explore the design of trading systems and the impact of investor behavior on market trends [23–25]. We use the agent-based modeling to construct a theoretical model of the order book of the stock index futures market, and then we calibrate the microbehavior of speculators, arbitrageurs, and hedgers in the market to match the trading mechanism, investor behavior, and investor structure of the real stock index futures market. We then calibrate the link between the futures market and spot market models and explore the influence of heterogeneous investors in the two markets. We find that speculators, arbitrageurs, and hedgers each play different roles in the stock index futures and spot markets, thereby exerting different influences on the operation of these two markets. While speculators serve as the foundation for other investors to participate in trading, both arbitrageurs and hedgers significantly reduce volatility and enhance price efficiency in the spot market, thereby playing a positive role in the operation of this market. From the perspective of investor behavior, we develop a model and explain how the stock index futures market can reduce spot market volatility. Our results may help regulators better understand the roles played by different types of investors in China's stock index futures market.

Given the unique benefits of agent-based modeling, we employ this methodology in our research. Our principal contributions are the following: First, our work is founded on a computational experimental methodology to model the stock index futures order book market and investigate the impact of various types of investors on the quality of futures in the stock index futures market. Second, our work is the first to model speculators, arbitrageurs, and hedgers in two markets and to model their trading behavior. Third, to accurately portray investor behavior, we conducted a linkage test between the futures market and the spot market. Fourth, we also evaluated the impact of the behavior of three types of investors in two markets. Our research contributes to the expanding body of knowledge on agent-based modeling approaches to trading system design and serves as a point of reference for similar studies being conducted in other nations' capital markets.

The remainder of the paper is structured as follows: In the second section, we separately model the spot and futures markets. In the third section, the cross-market benchmark model is calibrated. The fourth section contains the primary results and the discussion. The conclusion is the fifth section.

2. An Agent-Based Model of the Futures Market and Spot Market

2.1. Underlying Assets and Trading Mechanism of the Spot Market

2.1.1. Spot Market's Underlying Assets. In this paper, we design three spot underlying assets: fundamental value low volatility Stock L, fundamental value medium volatility Stock M, and fundamental value high volatility Stock H. The equity is set to 2,000,000,000 shares, the initial price is set to

20 yuan, and the volatility of the fundamental value is set to 4 basis points (bps), 8 bps, and 12 bps, as shown in Table 1. The investor also has cash assets with a daily risk-free interest rate of $r = 4\%/360$.

2.1.2. Order Book for the Spot Market. To make the model more consistent with the characteristics of the real market, we present a pure limit that meets the following characteristics:

(1) Each stock has an independent order book, and the market contains a total of three order books.

(2) There is no price limit.

(3) The minimum quotation unit is set to 1 cent.

(4) After the close of each trading day, the order book is cleared.

(5) The opening price of the stock on each trading day is the closing price of the stock on the previous trading day, and the current price is the most recent transaction price. If there is no transaction in the current period, the current price is equal to the previous price.

Each simulation cycle represents 5 minutes in the real market. As the trading time of each trading day in the Chinese stock market is 4 hours, there are 48 simulation cycles in the model corresponding to one trading day.

2.2. Underlying Assets and Trading Mechanism of the Stock Index Market

2.2.1. Stock Index Market's Underlying Assets. The purpose of a continuous futures contract is to connect all main contracts to facilitate a continuous analysis of contract data. This main continuous contract has the characteristics of high activity, large positions, and high turnover. As such, our paper establishes a stock index continuous futures contract model with specific parameters designed to meet the basic parameter characteristics of the CSI 300 stock index futures contract, as shown in Table 2.

2.2.2. Order Book for the Stock Index Market. The stock index futures market designed in our paper adopts a limit order book mechanism. The basic trading rules conform to the main characteristics of the Chinese stock index futures market. The specific trading rules are as follows:

(1) $T+0$ trading, no price limit (to exclude the effect of the different trading regimes in the two markets on the results, both the spot and stock index futures markets use the $T+0$ trading mechanism, and neither of them sets the price limit. A study on the impact of different trading mechanisms on market quality can be found in the groundwork of this paper's study [26]).

(2) Cash delivery.

(3) No position limit.

Table 1: Design of the spot underlying assets in the agent-based model.

Assets	Equity (shares)	Initial price (yuan)	Value fluctuations (bps)
L	2,000,000,000	20	4
M	2,000,000,000	20	8
H	2,000,000,000	20	12

Table 2: Stock index futures contract in the agent-based model.

Mechanism	Parameter design
Quotation unit	Index points
Contract multiplier	300 yuan per point
Tick size	0.2 yuan
Margin level	15% of the contract value
Contract duration	50 trading days

(4) Minimum order size of 1, with no limit on the maximum order size.

(5) Adopting margin and mark-to-market systems.

Each simulation period corresponds to 5 minutes in the real market, and each trading day has 4 hours of trading. As such, one trading day equates to 48 simulation periods.

2.3. Modeling Spot Market Investors.

Based on the method of Chiarella et al. [27], we model the mixed heterogeneous beliefs of spot market investors and draw on the practice of Zhao et al. [24]. We forecast and modeled spot market investors' wealth for adaptive asset allocation. In the model, the investor's order placing process still considers retained earnings μ. The order prices are all predicted prices based on retained earnings, and the order types are mainly determined based on both the investor's predicted price for the stock and the actual state of the order book. The investor's specific order placing rules are shown in Table 3.

The size of an investor's order submission is determined primarily by the investor's adaptive asset allocation process and the price at which the investor places an order. The order size submitted by investor i for asset j is the ratio of the absolute value of the current period's wealth change in asset j, $|w_{t+\tau}^{i,j} - w_t^{i,j}|$, to the investor's order placement price, $p_{\text{sub}}^{i,j}$, as shown in

$$q_t^{i,j} = \frac{\left|w_{t+\tau}^{i,j} - w_t^{i,j}\right|}{p_{\text{sub}}^{i,j}}. \tag{1}$$

2.4. Modeling Investors in the Stock Index Futures Market.

Based on their roles in the stock index futures market, we divide investors into three categories: speculators, arbitrageurs, and hedgers. Speculators only trade in the stock index futures market, whereas arbitrageurs and hedgers trade in both the spot market and the stock index futures market. This section focuses on modeling speculators, and Section 3 models the other two types of investors.

Table 3: Investors' order.

Direction	Order conditions	Order type	Price
Buy	Seller's order book is not empty and $p_{t+\tau}^{i,j} - \mu \geq \alpha_t^j$	Market order	$p_{\text{sub}}^{i,j} = p_{t+\tau}^{i,j} - \mu$
	Other types	Limit order	$p_{\text{sub}}^{i,j} = p_{t+\tau}^{i,j} - \mu$
Sell	Buyer's order book is not empty and $p_{t+\tau}^{i,j} + \mu \leq b_t^j$	Market order	$p_{\text{sub}}^{i,j} = p_{t+\tau}^{i,j} + \mu$
	Other types	Limit order	$p_{\text{sub}}^{i,j} = p_{t+\tau}^{i,j} + \mu$

As there is no dividend in the stock index futures market, speculators try to make a profit by taking the risk of investing in volatile markets. Indeed, in our model, speculators look for investment opportunities in a market that exhibits volatility.

2.4.1. Modeling Speculators' Price Forecasting Behavior. Let S_t be the stock index at time t, T is the duration of the stock index futures contract, d is the number of days the current contract has been traded, and r is the daily market risk-free rate. As a result, the theoretical value of stock index futures at time t, C_t, can be calculated as follows:

$$C_t = S_t \times \left(1 + r^{(T-d)}\right). \tag{2}$$

We distinguish between optimistic and pessimistic speculators, with optimistic speculators making bullish judgments on the futures market and pessimistic speculators making bearish judgments on the futures market. The predicted return r_t^0 of optimistic speculators for stock index futures at time t is

$$r_t^0 = \ln\left(\frac{C_t}{F_t}\right) + \theta + \varepsilon. \tag{3}$$

The predicted return r_t^p of pessimistic speculators for stock index futures at time t is

$$r_t^p = \ln\left(\frac{C_t}{F_t}\right) - \theta + \varepsilon, \tag{4}$$

where F_t is the price of stock index futures at time t, θ is investor sentiment, and ε is the noise term, which follows a uniform distribution of $[0, 0.005]$.

2.4.2. Speculators' Order Placing Rules. The direction of a speculator's order is determined by both the direction of their position and the forecasted return. When speculators' forecasted return is 0, they will buy when their position is greater than or equal to 0. The order placing rules are shown in Table 4.

The speculators' closing operations are based on their respective positions. As stock index futures trading is based on a margin trading system, speculators need to retain a certain amount of cash to deal with the risk of forced liquidation that may arise because of fluctuations in the futures market. In our model, the speculator opens a position using only a ω percentage of their cash assets (in our simulation experiment, ω is temporarily set to 30%), and the remaining cash assets are mainly used to deal with the risk of closing the position. Therefore, the volume of open orders q_t^i for speculator i at time t can be calculated as follows:

Table 4: Speculators' order placing rules.

Forecasted return	Position direction	Order direction
> 0	≥ 0	Buy open position
> 0	< 0	Buy close
< 0	≤ 0	Sell open position
< 0	> 0	Sell close

$$q_t^i = \frac{\omega * c_t^i / p_{\text{sub}}^i}{\text{CM/ML}}, \tag{5}$$

where c_t^i is the cash assets of investor i at time t, p_{sub}^i is the order price of investor i, CM is the index futures contract multiplier, and ML is the margin ratio.

The speculator's order price p_{sub}^i is the investor's forecast price after considering retained earnings. The investor's market order and limit order are determined by a combination of the speculator's forecast price for the stock and the actual state of the order book.

2.5. Modeling Cross-Market Investors

2.5.1. Arbitrageurs' Behavior. As a typical cross-market investor, an arbitrageur seeks price deviations and carries out risk-free arbitrage by comparing the theoretical price of stock index futures with the actual price. As there is no securities lending mechanism in the Chinese market (due to factors such as high thresholds for securities lending transactions, scarcity of securities lending targets, and high handling fees, securities lending transactions are more difficult to complete), we assume that an arbitrageur can only carry out positive arbitrage (i.e., sell short stock index futures and buy stock spot).

When an arbitrageur finds that the actual price F_t of stock index futures is higher than the theoretical price C_t and can cover its arbitrage cost μ, as shown in equation (6), it will enter the market to begin an arbitrage trade.

$$F_t > C_t(1 + \mu), \tag{6}$$

where μ is the arbitrage cost and follows a uniform distribution of $[0, 0.05]$ to reflect the different arbitrage costs.

Because of the low risk of futures arbitrage transactions, investors are not required to retain cash for the time being. In the model, an arbitrageur uses 50% of their cash assets to sell short stock index futures. Therefore, the quantity s_t^i of investor i short selling stock index futures at time t can be calculated as follows:

$$s_t^i = \frac{50\% * c_t^i / F_t}{\mathrm{CM/ML}}. \tag{7}$$

At the same time, the arbitrageur uses 50% of their cash assets to buy the corresponding number of components of the spot index so that the number $b_t^{i,j}$ of stocks j bought by investor i at time t is

$$b_t^{i,j} = 50\% \frac{* c_t^i * \mathrm{Cap}^j}{\sum_{j=L,M,H} \mathrm{Cap}^j} / p_t^j, \tag{8}$$

where c_t^i is the cash assets of investor i at time t, Cap^j is the equity of stock j, and p_t^j is the price of stock j at time t.

To assess the profit-taking exit of the arbitrageur, two scenarios are considered. First, the futures-spot spread in the market converges, and the arbitrageur leaves the market early by reaching its preset profit level. When arbitrageur i reaches their profit expectation η in advance at time t, as shown in equation (9), they consider closing their position early at that time.

$$W_t^i > \mathrm{WI}_{t_0}^i * \left(1 + \eta^i\right), \tag{9}$$

where t_0 denotes the start time of this arbitrage transaction, $\mathrm{WI}_{t_0}^i$ denotes the total wealth of investor i at time t_0, W_t^i denotes the total wealth of investor i at time t, and η^i denotes the predetermined profit expectation of arbitrageur i, which follows a uniform distribution of $[0, 0.05]$ reflecting its heterogeneity.

Second, if the arbitrageur does not reach their expected profit level, they will maintain their position until the contract expires and will end their arbitrage by taking delivery. In addition to modeling the main index futures contract, we model the delivery mechanism of the index futures market, which is a fundamental guarantee for risk-free arbitrageurs to take advantage of the futures market. During the contract settlement date (every 50 trading days), the stock index futures price will converge on the spot price. At this point, if an arbitrageur still has a position, they should buy and close the position and sell the spot position during the settlement date. Because the arbitrageur seeks immediate opportunities, all orders placed by that arbitrageur are market orders. In addition, to accurately record each gain of the arbitrageur, multiple simultaneous arbitrage transactions by a single arbitrageur are not allowed in the model.

2.5.2. Hedgers' Behavior. In addition to the cross-market investors discussed so far, we assess the role of hedgers. These actors focus on the spot market and trade in the stock index futures market primarily to hedge their spot positions. When a spot investor wants to hold a stock for a long time, they can use futures to hedge the downside risk and lock in their return.

Based on the mixed heterogeneous belief model proposed by Chiarella et al. [27], our model reflects the notion that an investor will engage in a future hedging transaction when their fundamental beliefs exceed a certain threshold ($y^i > a$). Furthermore, in our model, we assume that investors in this scenario pay more attention to the fundamental information of the stock in question and wish to hold the stock in the long term. As such, in this section, we model the trading behavior of hedgers in three steps.

Table 5: Order placing rules for hedgers.

Position	Order direction	Order quantity
$P_t^i > Q_t^i$ and $Q_t^i < 0$	Sell and open position	$P_t^i - Q_t^i$
$P_t^i < Q_t^i$ and $Q_t^i < 0$	Buy and close position	$Q_t^i - P_t^i$
$P_t^i < Q_t^i$ and $Q_t^i > 0$	Buy and open position	$Q_t^i - P_t^i$
$P_t^i > Q_t^i$ and $Q_t^i > 0$	Sell and close position	$P_t^i - Q_t^i$
$P_t^i > Q_t^i$ and $Q_t^i = 0$	Sell and close position	P_t^i
$P_t^i < Q_t^i$ and $Q_t^i = 0$	Buy and close position	$-P_t^i$
$P_t^i = Q_t^i$	No operation	0

First, we measure the risk exposure of hedgers. We choose β based on the capital asset pricing model (CAPM) to measure the risk exposure of a hedger's portfolio. As investors can hold multiple stocks simultaneously, we use the weighted average market value to calculate the overall β of the investor's portfolio, after calculating β of each stock. β of the portfolio held by investor i at time t can be calculated in the following way using β of each stock β_t^j ($j = L, M, H$) and the position:

$$\mathrm{portfolio\_}\beta_t^i = \sum_{j=L,M,H} \beta_t^j * \mathrm{rate}_t^{i,j}, \tag{10}$$

where $\mathrm{rate}_t^{i,j}$ is the ratio of the value of stock j held by investor i to the value of all stocks held by investor i at time t.

Second, we specify the hedger's asset allocation strategy. When investor i plans to buy stock j with a market value of $W^{i,j}$ at time t, hedging a transaction can be calculated to require the short sale of stock index futures worth $W^{i,j} * \beta_t^j * \mathrm{ML}$. However, the investor may submit a limit order. If that limit order cannot be filled immediately, the corresponding hedging transaction cannot take place at that time. Furthermore, given budget constraints, the investor must set aside the cash needed for the hedging transaction at the time the spot order is placed to ensure that the transaction can proceed. Therefore, the actual amount of the investor's stock purchase is $W^{i,j} - W^{i,j} * \beta_t^j * \mathrm{ML}$.

Third, we design the hedger's asset allocation. Based on the total value of the spot portfolio held by the hedger and its β, the position in the stock index futures market that should be held to hedge the spot position can be calculated as Q_t^i:

$$Q_t^i = -\mathrm{portfolio\_}\beta_t^i * \left[\frac{W_t^i}{(F_t * \mathrm{CM})}\right], \tag{11}$$

where W_t^i is the total value of the spot portfolio held by investor i at time t.

In addition, as the spot position of the hedger changes over time, it is necessary to adjust their position in the stock index futures market to reflect the actual situation. Table 5 compares the hedger's current position in the stock index futures market, P_t^i, with the position in the stock index futures market Q_t^i that the hedger should hold and determines the direction and volume of orders to be placed by the hedger.

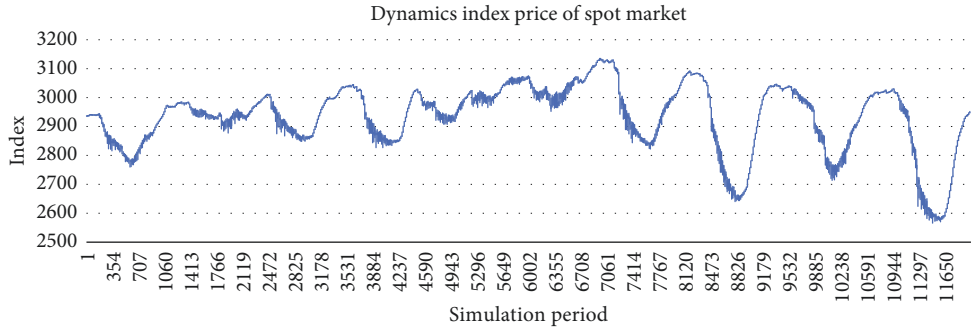

Figure 1: Dynamics index price of the spot market benchmark model.

When the investor's current position P_t^i is compared with Q_t^i, they will have the following operations: when the position is insufficient, the opening operation is carried out; if the position is found to be too large, the closing operation is carried out. Furthermore, depending on the investor's current position, the process of opening and closing a position is accompanied by varying buy and sell directions. For example, if the investor's current position is negative, the opening position will be a sell operation, and the closing position will be a buy operation. If the investor's current position is positive, the opening position will be a buy operation, and the closing position will be a sell operation. In addition, to ensure that the hedging transaction plays a real-time hedging role, the order types submitted by the hedger are market orders.

2.6. Model Specification and Simulations. Investors in our spot benchmark model all have heterogeneous beliefs, demonstrating 60% fundamental beliefs, 30% technical beliefs, and 10% noise beliefs, with the investor's adaptive transformation intensity set to 4. We use the initialization specification of spot market investors (including hedgers) suggested by Zhao et al. [24], and the initial cash availability of speculators and arbitrageurs is set to 1,000,000 yuan. Based on the spot benchmark model, we use an agent-based model to construct a stock index futures market. Experiment 1 simulates the investor structure of the stock index futures market to explore the cross-market quality impact of the stock index futures market on the spot market. Experiment 2 simulates a risk scenario with extreme volatility in the spot market and explores whether there is an asymmetric cross-market quality impact of stock index futures on the spot market under different risk conditions.

Each set of experiments in our work contains 30 simulations, each lasting 72,000 periods. One period in the simulated market corresponds to 5 minutes in the real stock market and the stock index futures market. Meanwhile, we select the data after a warmup; that is, we select the data of the last 12,000 periods in each simulation experiment, which is equivalent to 1 year (250 trading days) of trading data in the real market.

3. Cross-Market Benchmark Model Calibration

3.1. Spot Market Benchmark Model. In our study, a stock index is formed based on a multiasset spot, and a stock index futures market is then constructed based on the stock index.

Table 6: Market quality analysis using the spot market benchmark model.

	Stock L	Stock M	Stock H	Index
Volatility (bps)	42	47	62	32
Liquidity (yuan)	111,097,579	95,454,864	110,967,226	/
MAE (cents)	53	64	93	/
MRE (%)	2.63	3.23	4.42	/

Before analyzing the impact of the stock index futures market on the spot market, a benchmark model of the spot market is to develop first. Figure 1 shows the index series of the spot market benchmark model. The figure confirms the smooth running of the spot index.

In this section, we analyze the market quality of the benchmark spot market model from three perspectives: market volatility, market liquidity, and market price efficiency, respectively. The volatility indicator uses the standard deviation of the 5-minute price return, the liquidity indicator uses the Shanghai Stock Exchange liquidity index, and the market price efficiency indicator uses the absolute deviation (MAE) and relative deviation (MRE). Table 6 reports the results of the market quality analysis using the benchmark spot market model.

3.2. Investor Behavior Calibration. In the research about the stock index futures market, the behavior of arbitrageurs and hedgers is relatively objective, whose behavior is modeled consistently. In addition to arbitrageurs and hedgers, there is another key category of investors in the index futures market, known as speculators. Investors in this third category trade in a variety of ways, and their erratic behavior makes it difficult to use a standard model. In addition, speculators trade frequently and hold positions for short periods. As a result, this section focuses on calibrating the behavior of speculators.

Based on the modeling process of speculators described in the previous section, speculator sentiment θ is a key factor that dominates their trading behavior. As such, we focus on the analysis of this factor to test whether it can characterize, to some extent, the behavior of speculators. This section examines the impact of speculators with varying degrees of sentiment (0, 0.1%, 0.2%, 0.5%, 1%, 2%, 3%, 4%, and 5%) on the quality of the stock index futures market, and the

Table 7: The impact of speculator sentiment on the quality of the stock index futures market.

θ	Liquidity (yuan)	Volatility (bps)	MAE	MRE (%)
0	4,602,322	47	1,680	0.58
0.001	5,323,527	47	1,687	0.59
0.002	5,417,582	48	1,752	0.62
0.005	7,302,046	47	2,432	0.85
0.01	4,091,684	49	3,587	1.24
0.02	3,548,942	52	5,842	2.02
0.03	3,456,699	61	8,867	3.06
0.04	3,281,070	63	11,998	4.13
0.05	3,277,045	66	14,398	4.97

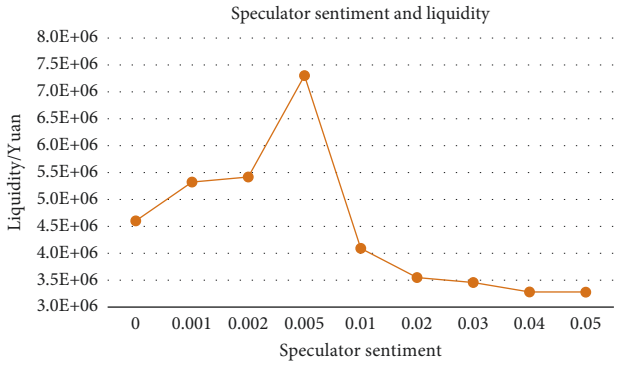

Figure 2: Trends in speculator sentiment and market liquidity.

statistical results are shown in Table 7. We find that the volatility of the stock index futures market significantly increases while market price efficiency significantly decreases as speculator sentiment increases.

Interestingly, as speculator sentiment increases, market liquidity first increases and then decreases, reaching its maximum when speculator sentiment arrives at 0.005, as shown in Figure 2. This phenomenon indicates that although moderate speculator sentiment can increase market liquidity, excessive speculator sentiment leads conversely to a decrease in liquidity.

In summary, when θ is 0.005, the stock index futures market features the lowest level of volatility, excellent liquidity levels, and the most efficient pricing. Given these results, the model effectively reflects the characteristics of the influence of speculators on market quality. As such, in all subsequent experiments in our work, $\theta = 0.005$ is used as the benchmark sentiment parameter.

3.3. Modeling the Investor Structure of the Stock Index Futures Market. Given that domestic stock index futures trading was launched only recently in China, it is currently difficult to obtain perfect data on the investor structure of the stock index futures market. According to the evolution process of investor types in HSI stock index futures proposed by Ding and Feng [4] in the 2005/2006 HSI stock index futures market, the proportions of speculators, hedgers, and arbitrageurs were 51.8%, 39.5%, and 8.7%, respectively. In the 2014/2015 HSI stock index futures market, the proportions of speculators, hedgers, and arbitrageurs were 44%, 42%, and 14%, respectively. These statistics demonstrate that, after nearly 10 years of development, the investment philosophy of investors in the HSI stock index futures market has become rational, with the proportion of speculators decreasing by 7.8%, the proportion of hedgers increasing by 2.5%, and the proportion of arbitrageurs fluctuating around 10%. Based on these numbers, we design the investor structure of the stock index futures model concerning the investor structure data of the HSI stock index futures market in 2014/2015. Based on the total number of investors in the model, the number of investors in each category is then calculated, as shown in Table 8.

3.4. Link Test of the Cross-Market Benchmark Model. Many studies show the existence of a bidirectional link between the stock index futures market and the spot market. For example, Yan et al. [28] find short-term two-way Granger causality between stock index futures prices and spot prices. Using 1-minute data from the first 2 months of the listings of the CSI 300 stock index futures as a sample, Hua and Liu [29] find a cointegration relationship and a bidirectional price guidance relationship between stock index futures prices and spot index prices. Based on daily data, Zhang et al. [30] find a bidirectional influence relationship between the spot and futures markets. Therefore, the relationship can be used as a formatting feature of the model in the construction phase. If the constructed stock index futures market and spot market can reproduce a formatting feature similar to that of the futures link, it indicates the model's high accuracy levels. This section, therefore, examines the modeled link between the spot market and the stock index futures market using Granger causality tests (before performing Granger tests, we conduct a unit root test on each data set and find them all to be first-order smooth series).

Figure 3 illustrates the price dynamics of the spot index and stock index futures. The price dynamics show a strong link between the two markets. We test this link further using Granger causality tests. While we mainly focus on the short-term relationship for high-frequency data, the 5th-order lags are used in this section. Table 9 reports the results of the Granger causality tests for stock index futures market returns and spot index returns. We find that both stock index futures market returns and spot index returns have Granger causality, which demonstrates the two-way link between the modeled stock index futures and spot markets.

4. Results

4.1. Impact of Speculators on the Quality of the Two Markets. This section discusses the results of five separate sets of experiments, each containing a different number of speculators: 500, 1,000, 2,000, 3,000, and 4,000, respectively. Each group contains 50% optimistic and 50% pessimistic investors, and speculator sentiment is set to 0.5%. As speculators only trade in the stock index futures market, we exclusively analyze the impact of speculators on the quality of this

Table 8: Design of the investor structure of the stock index futures model.

Percentage of investors (%)			Number of investors (persons)		
Speculators	Hedgers	Arbitrageurs	Speculators	Hedgers[1]	Arbitrageurs
44	42	14	2,200	2,100 (0.637)	700

[1]When the fundamental beliefs of spot investors are higher than a certain threshold, they engage in simultaneous futures hedging transactions. Therefore, the number of people engaging in futures hedging transactions has a one-to-one relationship with this threshold. In our paper, we first present the number of hedgers and then obtain the threshold value by inverse extrapolation from simulation experiments.

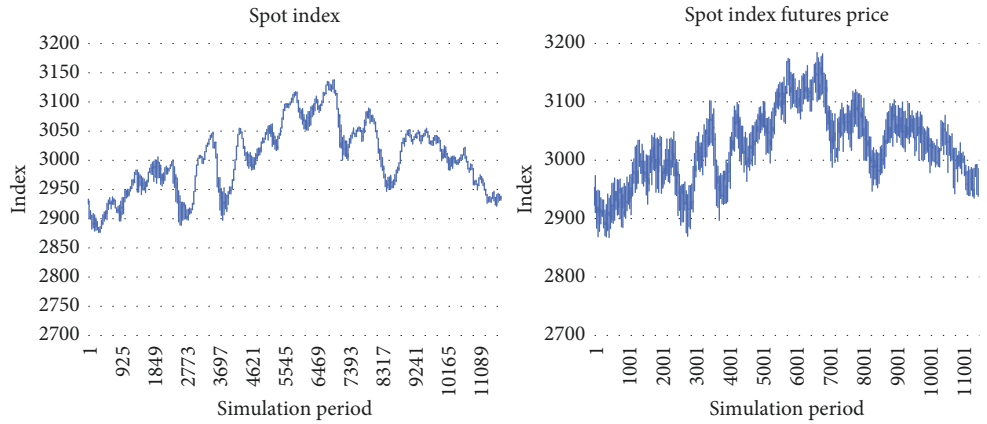

Figure 3: Price dynamics of the spot index and stock index futures.

Table 9: Granger causality tests for the two market returns.

H0	Lag order	*F*-statistic	*P* value	Judgment
Index ↛ future	1	369.307	0.000***	Reject H0
Future ↛ index	1	16.303	0.000***	Reject H0
Index ↛ future	2	237.352	0.000***	Reject H0
Future ↛ index	2	4.937	0.007***	Reject H0
Index ↛ future	3	164.444	0.000***	Reject H0
Future ↛ index	3	7.937	0.000***	Reject H0
Index ↛ future	4	128.414	0.000***	Reject H0
Future ↛ index	4	6.443	0.000***	Reject H0
Index ↛ future	5	104.899	0.000***	Reject H0
Future ↛ index	5	2.447	0.0318**	Reject H0

The symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 10: Impact of speculators of the stock index futures market.

Number of speculators	Liquidity (yuan)	Volatility (bps)	MAE (cents)	MRE (%)
500	3,627,883	45	2,803	0.99
1,000	4,890,928	47	2,724	0.95
2,000	7,302,046	47	2,432	0.85
3,000	9,634,527	48	2,404	0.83
4,000	10,881,574	48	2,395	0.83

market by assessing market liquidity, market volatility, and market price efficiency.

Table 10 reports the statistical results of the impact of the number of speculators on the quality of the stock index futures market. The results show that when the number of speculators increases, the volatility of the stock index futures market does not change much, and market price efficiency increases slightly. However, market liquidity increases significantly when the number of speculators increases, as shown in Figure 4.

We, therefore, argue that the presence of speculators leads to an increase in market price efficiency because an increase in the number of speculators leads to increased market competition, which in turn leads to an increase in market price efficiency (it is important to note that the results of this experiment do not take into account the effects

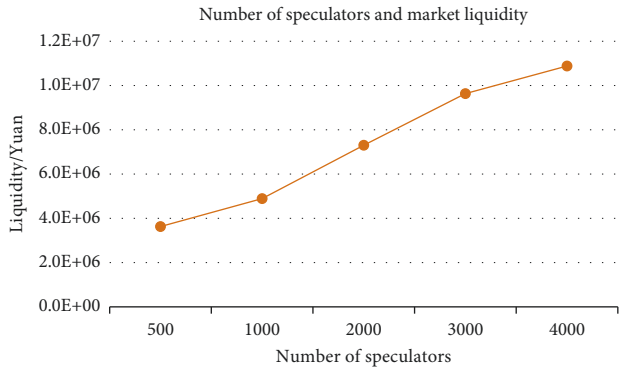

Figure 4: Trends in the number of speculators and market liquidity.

Table 11: Impact of arbitrageurs of the stock index futures market.

Number of arbitrageurs	Liquidity (cents)	Volatility (bps)	MAE (cents)	MRE (%)
0	7,302,046	47	2,432	0.85
500	7,405,144	47	2,377	0.82
1,000	7,288,207	47	2,377	0.82
2,000	7,341,010	46	2,362	0.82
3,000	7,584,439	45	2,335	0.81

Table 12: Impact of futures and cash arbitrageurs on spot market liquidity and volatility.

	Liquidity ($)			Volatility (bps)			
Numbers	Stock *L*	Stock *M*	Stock *H*	Stock *L*	Stock *M*	Stock *H*	Index
0	111,097,579	95,454,864	110,967,226	42	47	62	32
500	111,239,784	94,649,690	107,848,768	41	47	62	32
1,000	110,102,254	93,648,873	106,502,589	39	46	60	31
2,000	104,892,338	91,866,062	105,252,790	35	42	58	29
3,000	101,004,576	88,170,781	105,128,544	33	39	56	28

of speculator sentiment. The results of the previous experiments show that an increase in speculator sentiment leads to a decrease in market price efficiency). At the same time, an increase in the number of speculators significantly increases the liquidity of the stock index futures market. Then, we note that speculators play a positive role by injecting liquidity into the market, which in turn informs regulators' view of speculators in the stock index futures market.

4.2. Impact of Arbitrageurs on the Quality of the Two Markets. This section investigates the effect of arbitrageurs on the quality of the futures market. To this end, five separate experiments are designed, each containing a different number of arbitrageurs: 0, 500, 1000, 2000, and 3000. As speculators provide basic liquidity to the market to ensure its proper functioning, the experiments in this section are conducted in a market based on 1,000 speculators.

Table 11 reports the results of the experiment assessing the impact of the number of arbitrageurs on the quality of the stock index futures market. As the number of arbitrageurs increases, we note a trend of monotonic changes in both volatility and market price efficiency in the stock index futures market. This trend is evidenced by the fact that arbitrageurs reduce market volatility and enhance the price efficiency of the stock index futures market, but the extent of their effects on both variables is relatively small. As such, we speculate that this trend may be related to arbitrage opportunities in the market: if arbitrage opportunities are limited, arbitrageurs have little impact on the market. It is also important to note, however, that the arbitrage opportunities in the experiment are strongly related to the behavior of speculators (we do not believe that it is necessary to add the number of speculators to the market to increase the arbitrage opportunities in the market to study the arbitrage behavior of investors, because the arbitrage opportunities in the real market are extremely limited). Our results are not consistent with the findings of Xiong et al. [31], who find that arbitrageurs significantly affect the volatility of the stock index futures market. However, in their model, all investors except arbitrageurs are modeled from a spot market perspective, which differs significantly from how investors are modeled in our paper.

Table 12 reports the statistical results of the impact of the number of arbitrageurs on the liquidity and volatility of the spot market. The results show that the liquidity of the spot

Table 13: Impact of futures and cash arbitrageurs on price efficiency in the spot market.

	MAE (cents)			MRE (%)		
Numbers	Stock *L*	Stock *M*	Stock *H*	Stock *L*	Stock *M*	Stock *H*
0	53	64	93	2.63	3.23	4.42
500	52	64	91	2.60	3.26	4.35
1,000	49	61	90	2.52	3.08	4.30
2,000	43	55	83	2.15	2.78	3.94
3,000	39	49	78	1.95	2.48	3.72

Table 14: Impact of hedgers on the quality of the stock index futures market.

Numbers	Liquidity ($)	Volatility (bps)	MAE (cents)	MRE (%)
0	7,302,046	47	2,432	0.85
1,000 (0.748)	4,817,474	49	2,040	0.69
2,000 (0.644)	3,335,129	49	1,757	0.59
3,000 (0.547)	2,036,627	50	1,484	0.50

Table 15: Impact of hedgers on spot market liquidity and volatility.

Liquidity ($)				Volatility (bps)			
Numbers	Stock *L*	Stock *M*	Stock *H*	Stock *L*	Stock *H*	Stock *H*	Index
0	111,097,579	95,454,864	110,967,226	42	47	62	32
1,000 (0.748)	104,466,915	97,801,384	118,416,850	23	31	49	23
2,000 (0.644)	93,847,230	10,2856,000	121,473,796	11	20	38	16
3,000 (0.547)	96,902,078	11,3637,018	124,186,136	11	19	37	15

market does not change much as the number of arbitrageurs increases. We argue that as arbitrageurs exploit the timeliness of arbitrage opportunities, they use market orders, a practice that affects market liquidity. The weak change in market liquidity can therefore be explained by the fact that arbitrageurs essentially provide liquidity to the market, which is consumed by the market-priced orders they place. At the same time, as the number of arbitrageurs increases, market volatility decreases significantly, and arbitrageurs serve to stabilize the spot market. Table 13 reports the statistical results on the impact of the number of futures arbitrageurs on the pricing efficiency of the spot market. The results show that, with the increase in the number of futures arbitrageurs, the pricing efficiency of the spot market increases significantly, and the futures arbitrageurs have a positive impact on the spot market.

4.3. Impact of Hedgers on the Quality of the Two Markets. In this section, four separate sets of experiments are designed to explore the effect of hedgers on the quality of the futures market. Each experiment contains a different number of hedgers: 0, 1000, 2000, and 3000. The experiments in this section are also conducted in a market based on 1,000 speculators.

Table 14 reports the results of the effect of the number of hedgers on the quality of the stock index futures market. An increase in the number of hedgers significantly reduces the liquidity of the stock index futures market, which indicates that hedgers are liquidity consumers in the stock index futures market. At the same time, the price efficiency of the stock index futures market significantly increases when the number of hedgers increases.

Table 15 reports the statistical results of the impact of the number of hedgers on the liquidity and volatility of the spot market. The results show that spot market volatility decreases significantly when the number of hedgers increases and that hedgers play a stabilizing role in the market.

Table 16 reports the statistical results of the impact of the hedgers' number on price efficiency in the spot market. The results show that hedgers significantly improve price efficiency in the spot market.

In Table 17, "+" indicates that this category of investors has a positive impact on market quality, "−" demonstrates that this category of investors hurts market quality, and "/" illustrates that this type of investor has little influence on market quality. It is clear from the table that both arbitrageurs and hedgers have a positive effect on the spot market by reducing market volatility and improving market price efficiency.

Table 16: Impact of hedgers on price efficiency in the spot market.

	MAE (cents)			MRE (%)		
Numbers	Stock *L*	Stock *M*	Stock *H*	Stock *L*	Stock *M*	Stock *H*
0	53	64	93	2.63	3.23	4.42
1,000 (0.748)	22	33	63	1.11	1.68	3.00
2,000 (0.644)	9	19	41	0.45	0.93	1.94
3,000 (0.547)	8	16	38	0.45	0.86	1.82

Table 17: Impact of different types of investors on the quality of the futures and cash markets.

		Liquidity ($)	Volatility (bps)	Price efficiency
Speculators	Stock index futures market	+	/	+
Arbitrageurs	Stock market	/	+	+
	Stock index futures market	/	/	/
Hedgers	Stock market	/	+	+
	Stock index futures market	−	/	+

5. Conclusion

We use agent-based modeling to construct an order book model for stock index futures and investigate the impact of different types of investors in the stock index futures market on the quality of the two markets. Our study is the first to comprehensively model the trading behavior of speculators, arbitrageurs, and hedgers in the stock index futures market. In addition, in terms of investor behavior calibration, we calibrate speculators whose trading behavior is more subjective. In terms of model calibration, we perform the first link test on the cross-market model. Through simulations, we find that speculators, arbitrageurs, and hedgers play different roles in the market and that they have different effects on the operational quality of the futures market. While speculators provide liquidity to the stock index futures market and form the basis for other investors to participate in market transactions, both arbitrageurs and hedgers have various effects on the spot market, including significantly reducing volatility, enhancing price efficiency, and playing a positive role in operational quality. It is hoped that our results will help regulators understand the roles played by different types of investors in the stock index futures market from the perspective of market participants' behavior. Our research contributes to the expanding body of knowledge on agent-based modeling approaches to trading system design and serves as a point of reference for similar studies being conducted in other nations' capital markets.

Data Availability

Our research methodology can be simply understood as a "simulation" and does not involve real market data.

Disclosure

The views expressed in this paper are those of the authors and do not necessarily represent the views of the Shenzhen Stock Exchange.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] H. Q. Chen and C. H. Zhang, "Does index futures trading reduce stock market jump. Risk?- evidence from the Chinese stock market," *Economic Research Journal*, vol. 50, no. 1, pp. 153–167, 2015.

[2] H. Miao, S. Ramchander, T. Wang, and D. Yang, "Role of index futures on China's stock markets: evidence from price discovery and volatility spillover," *Pacific-Basin Finance Journal*, vol. 44, pp. 13–26, 2017.

[3] Q. Han and J. Liang, "Index futures trading restrictions and spot market quality: evidence from the recent Chinese stock market crash," *Journal of Futures Markets*, vol. 37, no. 4, pp. 411–428, 2017.

[4] Y. J. Ding and Y. Feng, "Analyzing the impact of stock index futures trading limits on. market quality during abnormal fluctuations in the spot market," *System Engineering Theory and Practice*, vol. 37, no. 10, pp. 2481–2496, 2017.

[5] Y. Q. Huang, C. Y. Wang, and X. X. Cui, "Is the control of index futures effective?-from the perspective of spot market volatility," *Studies of International Finance*, vol. 337, no. 9, pp. 87–96, 2018.

[6] M. T. Wang, X. M. Sun, and Y. Chen, "Jump effects of stock index futures on its underlying. spot index in China: a perspective of synchronous and extending trading," *Journal of Management Science in China*, vol. 21, no. 8, pp. 64–82, 2018.

[7] H. Mou and S. X. Yuan, "Is the stock index futures the main factor for the abnormal fluctuation of the spot market?-an empirical study based on the SSE 50 index and the CSI 500 index," *Modernization of Management*, vol. 38, no. 03, pp. 12–15, 2018.

[8] Z. H. Jian, P. J. Deng, K. Y. Luo, and Z. Zhu, "The effect of market quality on the causality between returns and

volatilities: evidence from CSI 300 Index futures," *Journal of Management Science and Engineering*, vol. 3, no. 1, pp. 16–38, 2018.

[9] National Institute of Finance and Tsinghua University, "Improve the design of the system to enhance market confidence to build a long-term healthy and stable development of the capital market," *Tsinghua Financial Review*, vol. 12, pp. 14–23, 2015.

[10] X. Wang, X. Wang, B. Li, and Z. Bai, "The nonlinear characteristics of Chinese stock index futures yield volatility: based on the high frequency data of CSI300 stock index futures," *China Finance Review International*, vol. 10, 2019.

[11] S. Cao, Z. Li, K. G. Koedijk, and X. Gao, "The emotional cost-of-carry: Chinese investor sentiment and equity index futures basis," *China Finance Review International*, vol. 12, no. 3, pp. 451–476, 2022.

[12] Z. Y. Tu and M. Guo, "A theoretical analysis of the impact of stock index futures launches on spot market prices," *Journal of Financial Research*, vol. 10, pp. 104–116, 2008.

[13] X. H. Chen, "An empirical analysis of stock market volatility before and after the listing of CSI 300 stock index futures," *Management World*, vol. 3, pp. 174-175, 2012.

[14] J. L. Li, Y. Lei, and S. J. Li, "Market depth, liquidity, and volatility-the impact of CSI 300 stock index futures launch on the spot market," *Journal of Financial Research*, vol. 6, pp. 124–138, 2012.

[15] G. X. Qiao, Q. Liu, and M. J. Zhang, "The impact of CSI 300 index futures on the continuous volatility and jump volatility of the cash market in China," *Chinese Journal of Management Science*, vol. 22, no. 10, pp. 9–18, 2014.

[16] X. Y. Zhang and Z. H. Shen, "The impact of introduction of stock index futures on China's stock market volatility: empirical analysis based on high-frequency data of HS300 index futures," *Review of investment Studies*, vol. 30, no. 10, pp. 112–122, 2011.

[17] H. W. Xu and C. F. Wu, "Did the introduction of CSI 300 index futures improve the quality of spot market: an empirical study based on simultaneous-equations model," *Nankai Business Review*, vol. 15, no. 4, pp. 101–110, 2012.

[18] W. Zhang, Y. J. Zhang, and X. Xiong, *Agent-based Computational Finance: An Alternative Way to Understand the Market*, Science Press, Beijing, 2010.

[19] V. Darley, A NASDAQ market simulation: insights on a major market from the science of complex adaptive systems, vol. 1, World Scientific, Singapore, 2007.

[20] Y. L. Li, W. Zhang, and X. Xiong, "Impact of tick size on market liquidity by agent-based modeling approach," *Journal of Management Science*, vol. 25, no. 1, pp. 92–98, 2012.

[21] L. J. Wei, "An agent-based model for the impact of the $T+0$ trading mechanism on market quality," *Journal of Management in China*, vol. 19, no. 11, pp. 90–102, 2016.

[22] L. Wei, W. Zhang, X. Xiong, and L. Shi, "Position limit for the CSI 300 stock index futures market," *Economic Systems*, vol. 39, no. 3, pp. 369–389, 2015.

[23] X. Xiong, Y. Cui, X. Yan, J. Liu, and S. He, "Cost-benefit analysis of trading strategies in the stock index futures market," *Financial Innovation*, vol. 6, no. 1, p. 32, 2020.

[24] R. Zhao, Y. Cui, and X. Liu, "Tick size and market quality using an agent-based multiple-OrderBook model," *Frontiers in Physics*, vol. 8, no. 135, pp. 1–8, 2020.

[25] Y. A. Cui, X. Xiong, L. J. Wei, and S. Y. He, "Agent-based modeling from the perspective of FinTech," *System Engineering Theory and Practice*, vol. 40, no. 2, pp. 373–381, 2020.

[26] X. Xiong, J. Liang, Y. A. Cui, W. Zhang, and Y. Zhang, "Analysis of the spot market's T+1 trading system effects on the stock index futures market," *Eurasia Journal of Mathematics, Science and Technology Education*, vol. 13, no. 12, pp. 7679–7693, 2017.

[27] C. Chiarella, G. Iori, and J. Perelló, "The impact of heterogeneous trading rules on the limit order book and order flows," *Journal of Economic Dynamics and Control*, vol. 33, no. 3, pp. 525–537, 2009.

[28] M. Yan, S. S. Ba, and B. Wu, "Price discovery and volatility spillovers of stock index futures markets in China," *Systems Engineering*, vol. 27, no. 10, pp. 32–38, 2009.

[29] R. H. Hua and Q. F. Liu, "The research on price discovery ability between stock index market and stock index spot market," *The Journal of Quantitative & Technical Economics*, vol. 10, pp. 90–100, 2010.

[30] F. He, W. Zhang, X. Xiong, X. T. Zhang, and W. Meng, "Research on the relationship between CSI300 stock index futures and its underlying stock index," *Journal of Systems Engineering*, vol. 32, no. 5, pp. 648–659, 2017.

[31] X. Xiong, W. Zhang, Y. J. Zhang, J. Liu, and H.-C. Xu, "Analyzing the impact on stock index futures market volatility of arbitrage," *Systems Engineering-Theory and Practice*, vol. 34, no. 3, pp. 623–630, 2014.

[32] R. Y. Tan and M. N. Sheng, "Will stock index future affect the volatility of stock market?" *Contemporary Finance & Economics*, 2011.

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Research Article

Do Local and World COVID-19 Media Coverage Drive Stock Markets? Time-Frequency Analysis of BRICS

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The role of media coverage as a proxy for investor sentiments has led to the assessments of the impact of COVID-19 media coverage on financial markets. To determine how both local and global media coverage affect financial markets differently, we investigate this issue from the perspective of top emerging markets, BRICS (i.e., Brazil, Russia, India, China, and South Africa). With datasets covering January 2020 to March 2022, we employ the wavelet coherence technique on two major subsamples, viz. initial outbreak year sample and the "new normal" era sample. Our findings demonstrate the leading role of BRICS equities in the initial outbreak period, particularly across medium and low frequencies. In the "new normal" era, we find a significant effect of world media coverage on BRICS equities. We discuss the implications of our findings, which are of importance to investors, policymakers, and practitioners.

1. Introduction

In the 21st century, the global financial crisis (GFC) had the most devastating effects on global markets until the emergence of the COVID-19 pandemic. Having occasioned a strange and unprecedented financial market meltdown, the COVID-19 pandemic's effect is noted to exceed the hardships during the era of the GFC [1]. Since its inception, notable financial markets have registered record-breaking losses, with some losses continuing as various strands of the virus emerged.

Accompanied by rigid restrictions such as social distancing, shutting of face-to-face school sessions, ban on international travels, closure of borders and places of worship, etc., measures to combat the spread of the COVID-19 and mitigate the associated hardships on the global economy resulted in a heightened concentration on media information across several outlets. To facilitate acceptance of policy measures against the ravaging impact of the pandemic and boost economic recovery, the pivotal role of media coverage has been underscored. Complexities in capital markets and society have been proxied with data on investor sentiment [2–4]. At the societal level, behavioral factors like public mood and/or investor sentiment are best captured by media data, and this is particularly applicable in the era of a long-lasting pandemic, where diverse capital market reactions have been witnessed regardless of market size, market bloc, or investment class, although the magnitudes of the effect may differ.

Hinged on the abovementioned rationale, we analyze the impact of COVID-19 media coverage on a market bloc containing major five emerging economies whose assets are noted to be instrumental to international portfolios due to their returns predictability and high-yielding characteristics [5, 6]. The economies of Brazil, Russia, India, China, and South Africa (i.e., BRICS) form a vibrant market bloc with lucrative growth prospects. With their substantial contribution to the global economy and their pivotal contribution to international portfolios, examining the effect of COVID-19 media coverage on their equity markets is necessary to

inform market participants of how behavioral factors tend to impact the price-generating mechanism of emerging market equities [6, 7].

Specifically, we examine the co-movement dynamics between media coverage and BRICS equities. Motivated by recent studies under the wavelet framework, we employ the bi-wavelet time-frequency approach, which is capable of revealing the lead-lag interrelationships between media coverage and equity prices across both the time and frequency domains.

The main motivation for the study stems from investors' and broader financial market participants' desire to search for assets with better returns and risk profiles during a systemic crisis such as the COVID-19 pandemic. In particular, the integration of asset markets over recent times coupled with the frequency of financial crises has contributed to the scarcity of such assets. Within this broader framework, the role of investor sentiment on asset returns and particularly the immunity of various assets against such returns is gaining a lot of attention as well. Thus, in this paper, we attempt to study the interrelation of media sentiment driven by the COVID-19 pandemic in five major emerging market economies by accounting for both local and international media coverage. We focus on the BRICS economies owing to their global significance as the major emerging market economies, their global trade share and the attractiveness of their financial markets to potentially offer high mean returns, which contribute to higher risk-adjusted performance for investors from developed markets. To the best of our knowledge, this is the first study to document this interrelation.

We offer specific contributions as follows. First, from an emerging market bloc, we provide the time-frequency dynamics of the lead-lag relationships between COVID-19-related media coverage and equity prices. While the time-domain trajectory of the co-movements between information, investor sentiments, and equity prices is essential, the heterogeneity of financial market participants [8, 9, 10] suggests that revealing the interrelations between these variables along frequency bands, which correspond to trading horizons, is of importance to market participants whose decisions are heterogeneous across the short-, medium-, and long-term trading periods.

Second, we tackle the impact of the pandemic on emerging markets equities from the behavioral viewpoint, which makes our study contribute to the strand of works that examine the behavioral impact of the pandemic on financial markets. It is to be noted that public mood and/or investor sentiments tend to intensify during stressed market conditions, but assessments of the pandemic's impact are fixed. The ubiquity of COVID-19 shocks was clear from the pandemic's onset following the intensity of the repercussions experienced by top-international markets like CAC40, DJIA, and S&P500 and emerging markets such as NSE50 [11]. While much empirical analysis has focused on top listed markets [12–16], the impact of the pandemic on the capital markets of emerging economies is yet to be analyzed in the context of behavioral variables such as public mood and/or sentiment.

Third, we undertake a comparative analysis of the respective effects of local and world media coverage on each of the BRICS equities. Several works have employed different proxies for the COVID-19 pandemic's effect. Amongst them are death counts, the number of confirmed cases, media coverage index, and the pandemic fear index [13, 17]. We add to the class of literature that examines the pandemic's impact using media coverage and we do this for both local and global media coverage. By doing so, we present evidence of both locally and internationally driven public mood and/or investor sentiments' impact on equity markets.

Methodically, relative to other approaches, the wavelet coherence approach has several benefits; hence, its application in this study. First, it can reveal information about variables' joint behavior not only within a single domain of time but also across distinct investment time scales or frequency bands, allowing us to investigate various patterns of BRICS equities and media coverage movements, lead-lag connections, and co-movements. We use wavelet approaches since the co-movements and lead-lag relationships between investor sentiments and equity prices across frequency bands, which represent investment horizons, are so important in this case. Second, strict assumptions like stationarity, linearity, or nonlinearity of the data series, which may be so significant to overlook in other techniques, are not primary to the wavelet technique. As a result, it can be applied to both linearly and nonlinearly distributed series. Third, for both short and long-time series data, the wavelet technique is efficient in deciphering crucial findings. All the aforementioned features portray the wavelet approach as a robust technique for investigating various time series' coherence, which we employ to investigate the causal relationships between variations in local and world COVID-19 media coverage indices (MCI) and BRICS equities.

Through our bi-wavelet analysis, we revealed that the patterns of co-movement between MCI and each of the BRICS equities are generally comparable. In the first year of the COVID-19 pandemic, BRICS markets provided modest protection against COVID-19 shocks, as measured by both local and global MCI at medium and low frequencies, which roughly correlate to monthly and quarterly trading periods. Conversely, we found more complicated co-movement dynamics between media coverage and BRICS stocks in the "new normal" era. We find that global COVID-19 media coverage drives and offers large risks to developing market stocks at medium and low frequencies in the new normal.

The remaining parts of the study are organized as follows. Section 2 describes our datasets and the wavelet technique. We discuss the main results and their implications in Section 3 and conclude in Section 4.

2. Datasets and Methods

2.1. Data and Descriptive Statistics. Our analysis makes use of daily stock indices of BRICS economies and both world media coverage indices (WMCI) and local media coverage indices (LMCI). Our datasets span between January 2020 and March 2022. The datasets on BRICS equities were sourced from Bloomberg, whereas the LMCI and WMCI

were sourced from RavenPack. The MCI from Ravenpack quantifies COVID-19-related media coverage as the proportion of news sources related to the COVID-19 pandemic to total news sources. With a base of 0% and a limit of 100%, higher MCI indices indicate higher levels of news coverage on COVID-19. We account for both local and international media coverage due to the systemic nature of the pandemic. We argue that both local and international sentiments may have an impact on the financial markets; therefore, accounting for both these metrics is important for a better understanding of the impact of various media coverage-driven news sentiments on financial markets. The statistical properties of the sample are summarized in Table 1. Figure 1 shows plots that depict the trajectories of each BRICS equity indices, their corresponding LMCI, and the WMCI. We notice that at the outbreak of the pandemic, all countries experienced a sharp decline in equities. Thus, underscoring the global nature of the pandemic and its systemic effects on the global financial markets. This sharp decline coincides with a sharp increase in the local and local MCI for each country. However, in the following months, we will see different patterns across different markets, accounting for the various waves of the pandemic. For instance, China experienced a sharp decline around 2021 due to a rise in pandemic cases again. However, we point out that the large decline in Russian equities at the end of the sample period may be attributed to the geopolitical crisis rather than the pandemic.

2.2. Methods. We apply the squared wavelet coherence (S-WC) and wavelet phase difference (WCPD) techniques in this study. The use of these wavelet methodologies is consistent with the steps of References [18, 19], as propagated in recent literature [20]. The wavelet transform is utilized to get the S-WC. The approach emerges from a bivariate model hinged on a continuous wavelet transform (CWT) that is capable of revealing varied scale localizations [21].

We start with the Morlet wavelet, which was proposed with the continuous wavelet transform by Morlet et al. [22, 23] and Goupillaud et al. [24]. The Morlet wavelet may be written as follows:

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}. \tag{1}$$

One can see that the Morlet wavelet consists of a complex sine wave within a Gaussian envelope. In line with the existing literature, we employ continuous wavelet transformation.

To generate the CWT of two separate time series, say $a(t)$ and $b(t)$, we follow Reference [18] to generate the S-WC between $a(t)$ and $b(t)$ from their individual CWTs, $W_n^a(u,s)$ and $W_n^b(u,s)$, respectively, as follows:

$$W_n^{ab}(u,s) = W_n^a(u,s)^* W_n^b(u,s), \tag{2}$$

where u denotes location, s represents scale, and the complex conjugation is represented by *. The CWT facilitates differentiation of the regions in the time-frequency domain, embodied by the co-movements between $a(t)$ and $b(t)$, even in the absence of their common strong power. Put differently, at every wavelet scale, the CWT depicts the localized covariance between $a(t)$ and $b(t)$. So, a CWT estimate near 1 suggests that $a(t)$ and $b(t)$ are highly synchronized, whereas a CWT estimate of 0 denotes a lack of significant synchronization.

Following [19], the S-WC, which defines the co-movements between $a(t)$ and $b(t)$ is defined as follows:

$$R^2(u,s) = \frac{S\left(s^{-1}\left|W^{ab}(u,s)\right|^2\right)}{S\left(s^{-1}\left|W^{a}(u,s)\right|^2\right) S\left(s^{-1}\left|W^{b}(u,s)\right|^2\right)}, \tag{3}$$

where s denotes smoothing on the time-frequency scale. The S-WC parameters can be interpreted as a correlation measure in time-frequency space, with a range of values confined between 0 and 1. However, converse to the popular measure of the correlation between two sets of data arrays (i.e., the Pearson coefficient, with a range of values between −1 and 1), the S-WC by default, belongs to the 0 and 1 interval. As a result, it is unable to detect whether the examined return series moves in similar or opposing directions. That is, in distinguishing between negative and positive correlations, the S-WC cannot be relied upon.

To gain additional insights about the co-movement between $a(t)$ and $b(t)$ their lead-lag dynamics, the WCPD is introduced. The WCPD facilitates an efficient distinction between two plausible relations, i.e., negative and positive [18].

The WCPD can be expressed as follows:

$$\Phi_{ab}(u,s) = \tan^{-1}\left(\frac{\mathrm{Im}\left\{S\left(s^{-1}W^{ab}(u,s)\right)\right\}}{\mathrm{Re}\left\{S\left(s^{-1}W^{ab}(u,s)\right)\right\}}\right), \tag{4}$$

where Im (Re) represents imaginary (real) portions of the joint smoothed CWT.

A set of two data arrays with a null phase difference is an example of a perfectly co-moving time series. We adopted a standard visual representation of the data based on heat map panels to represent both S-WC and WCPD. In the S-WC heat maps, deep arrows reflect phase connections between any named two series (any of the BRICS equities and either LMCI or WMCI).

The data arrays act in either in-phase (positive correlation) or anti-phase (negative correlation) mode, portrayed by the left and right directional arrows, respectively. When an arrow points upward or downward, it signifies that $a(t)$ or $b(t)$ is ahead of $b(t)$ or $a(t)$, respectively, by $\pi/2$. Taking note of the guidelines given above facilitates deciphering the message covered by an arrow, regardless of the direction it points.

3. Results

Our empirical results from the S-WC and WCPD-based lead-lag relationships between local and world MCI for each of the BRICS economies are presented in this section. The co-movement patterns from which we infer lead-lag dynamics are presented in scalograms. All horizontal axes

Table 1: Descriptive statistics.

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Obs.
Panel A: Equities								
Brazil	4668.05	4713.9	5661.2	2879.57	580.57	-0.74	3.22	564
China	1003.54	1034.77	1196.05	756.8	100.25	-0.72	2.48	564
India	8099.96	8310.66	11136.44	4407.46	1842.88	-0.02	1.72	564
Russia	11697.64	11567.19	15275.38	7202.93	1892.41	0.06	1.86	564
South Africa	212658.1	220245.2	260408.4	130686.9	26635.88	-0.54	2.6	564
Panel B: MCI								
Brazil	60.85	66.32	90.4	0	20.39	-1.08	3.7	564
China	61.18	62.35	90.5	0	13.91	-1.32	7.42	564
India	59.29	63.02	83.9	0	15.56	-1.6	6.58	564
Russia	55.2	56.34	86.89	0	15.76	-1.04	5.26	564
South Africa	62.07	66.86	92.81	0	20.08	-1.32	4.54	564
World	65.85	69.75	82.95	0.09	13.94	-2.72	11.97	564

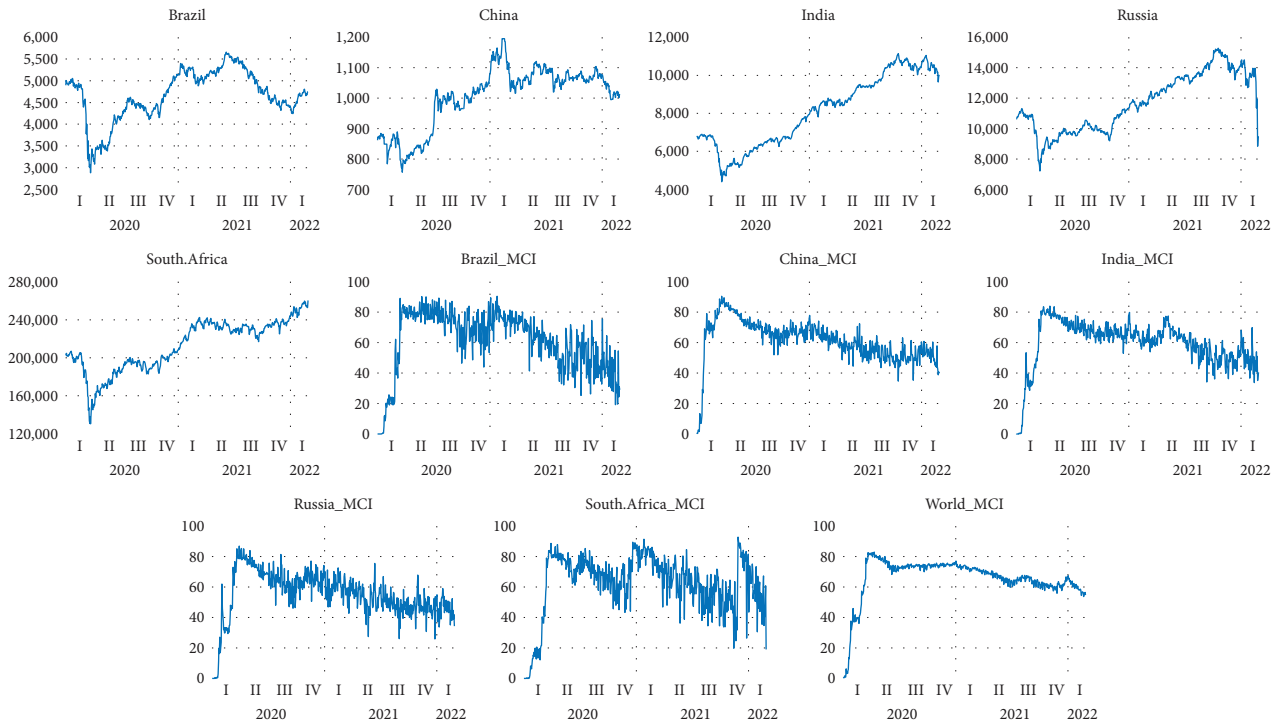

Figure 1: Time series plots.

display the time steps and the vertical axes portray the frequency, measured in days. Each scalogram is accompanied by a color bar, which represents a key for reading the scalogram. Generally, hotter colors, such as yellow and red, communicate high coherence, whereas warmer colors, such as green and blue, communicate low coherence. As detailed in the methods, the phase difference arrows pointing right (→) suggest an in-phase relationship and those pointing left (←) suggest an out-phase relationship. Right and up-diagonal (↗) or left and down-diagonal (↙) arrows indicate that the first variable (local or world MCI) is leading either of the BRICS equities. Right and down-diagonal (↘) or left and up-diagonal (↖) arrows indicate that the second variable (either of BRICS equities) is leading either local or world MCI. We emphasize the phase difference relationships that fall within the cone of influence (COI), which reveals the significant co-movement dynamics between the analyzed pairs.

For two subsamples, we focus on the initial outbreak year (i.e., 2020) and the "new normal" (i.e., from February 2021 to 2022). Thus, we analyze each BRIC equity market under two main sample periods.

3.1. Media Coverage and BRICS Equities in the Initial COVID-19 Outbreak Year (2020)

3.1.1. Media Coverage Index and Equities of Brazil in the Initial COVID-19 Outbreak Year. Figure 2 portrays the wavelet coherence plots for the co-movements between the

COVID-19 media coverage index and Brazilian equities in the first outbreak year.

From panel A, which reveals the scalogram for the coherence between Brazil MCI and Brazilian equities, we find that at a high-frequency scale of 2–4 days, between April to June 2020, the positioning arrows (↗) and (↙) signify that local MCI led its co-movement with Brazilian equities. This means that the dynamics of Brazilian equities were driven by MCI in the first few months of the pandemic. This period corroborates the period in which restrictive measures were initiated by several economies to curb the spread of the coronavirus. Intuitively, it is natural to assume that Brazilian equities will respond to local media coverage in the first few trading days of such months. These dynamics, despite changing across the median frequency bands, persisted between March and June 2020 across the 64 daily frequency bands and beyond. Notwithstanding, market dynamics changed after the first week of trade, between the 8–16 and 16–45 frequency bands, around May–June and November 2020. At such frequency bands, Brazilian equities instead led their co-movement with local media coverage. The high predictability of the pricing and return dynamics of emerging market equities may be a factor that influenced this co-movement despite the systemic crisis induced by the COVID-19 pandemic.

Concerning the world media coverage (panel B), interspersed positioning arrows are spotted across 2–8 daily scales, which correspond to the high-frequency bands. Notably, these arrows largely indicate either an antiphase relationship between world MCI and Brazilian equities or a leading role for world MCI. The antiphase relationship is more profound in March and November 2020 along the 2–3 daily scale. The intuition is that Brazilian equities negatively respond to world media coverage of COVID-19-related news. This is reasonable given that the early days of the pandemic resulted in intense negative impacts on several equity markets, and high-frequency bands are likely to experience hasty market dynamics. World MCI led Brazilian equities around June and between September and October 2020 across the 4–8 frequency band. Impliedly, as Brazilian equities lag world MCI, the market dynamics in Brazilian equities are driven by global COVID-19 media coverage. That is, the dynamics in emerging markets may follow from those factors that drive the dynamics of the world economy. Between November and January 2020, the positioning arrows suggest an in-phase relationship between world MCI and Brazilian equities beyond the monthly frequency band (32–45 days). Impliedly, as world COVID-19 media coverage increases, Brazilian equities increase correspondingly. The quest for emerging market assets in turbulent periods may explain this nexus. After investors realize that Brazilian equities may withstand COVID-19 shocks, the rush for Brazilian equities in lower frequency periods may push the price up, and hence, the positive relationship.

3.1.2. Media Coverage Index and Equities of Russia in the Initial COVID-19 Outbreak Year. Figure 3 portrays the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Russian equities in the first outbreak year.

Panel A of Figure 3 shows the coherence plot between local COVID-19 media coverage and Russian equities. At a high-frequency scale, specifically 2–4 days, the co-movement between Russian equities and local MCI exhibited an antiphase relationship in February, when COVID-19 was yet to be declared a pandemic by the World Health Organization (WHO). This persisted across the 4–5 daily frequency band in the same month with slight indications of Russian equities-driven co-movements, which saw a full manifestation in August 2020 with (↖) and (↘) positioning arrows at high frequencies (2–6 days). Similar dynamics are spotted between December 2020 and January 2021. Similar to Brazilian equities, the predictability of market dynamics of emerging markets assets explains the leading role of these equities. Across the weekly scale (8 daily frequency) in September 2020, straight-up positioning arrows signify that local MCI rather led Russian equities by $\pi/2$ and partly communicate the driving role of local COVID-19 media coverage, whereas the straight-down positioning arrows between the 12–16 daily frequency band in March 2020 communicated the driving role of Russian equities. Beyond these scales, up to a daily frequency of 24 hours, Russian equities remain the lead series ahead of COVID-19-related local media coverage.

Panel B of Figure 3 reveals the co-movement dynamics between world MCI and Russian equities. We find mixed co-movement and lead-lag dynamics between world MCI and Russian equities in the high-frequency bands (2–8 days). The antiphase relationships in February–March 2020 and November 2020 suggested an inverse relationship between media coverage and Russian equities in the early days of the COVID-19 outbreak and possibly, during new variant detection. This explains the leading role of world MCI ahead of Russian equities between July and August 2020 across 2–3 daily frequencies. After world MCI led Russian equities in March 2020 across the fortnightly scale (up to 16 daily cycles), we witness the leading (lagging) role of Russian equities (world MCI) across lower frequency bands.

3.1.3. Media Coverage Index and Equities of India in the Initial COVID-19 Outbreak Year. Figure 4 portrays the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Indian equities in the first outbreak year.

From the co-movement dynamics revealed by the coherence plot in Panel A of Figure 3, we find that across the high-frequency bands (2–4 daily scale), the market dynamics for Indian equities were driven by local COVID-19 media coverage. This was observable from January to July 2020 and persisted through the 2–16 daily frequencies. Up to 2 weeks of trading, the early days of the COVID-19 pandemic influenced several markets across the globe. Thus, it is unsurprising that the Indian equity market was driven by COVID-19 shocks, proxied by local media coverage. However, given the character of an emerging market like India, equities turned back to lead or drive COVID-19 media

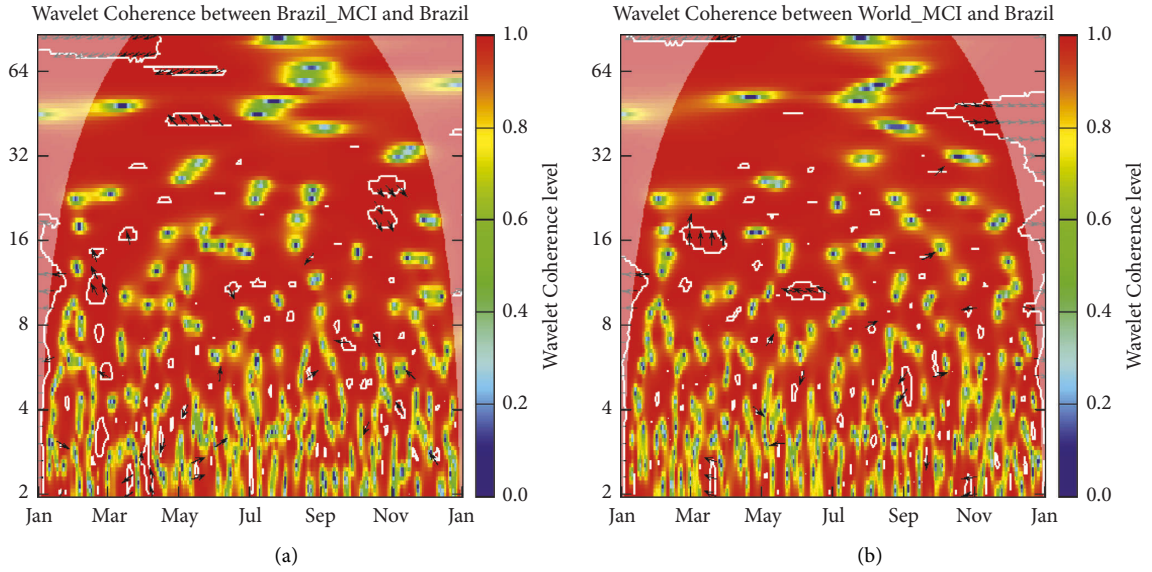

Figure 2: MCI and Brazilian equities in the initial COVID-19 pandemic year. The values on the x axis show the dates and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

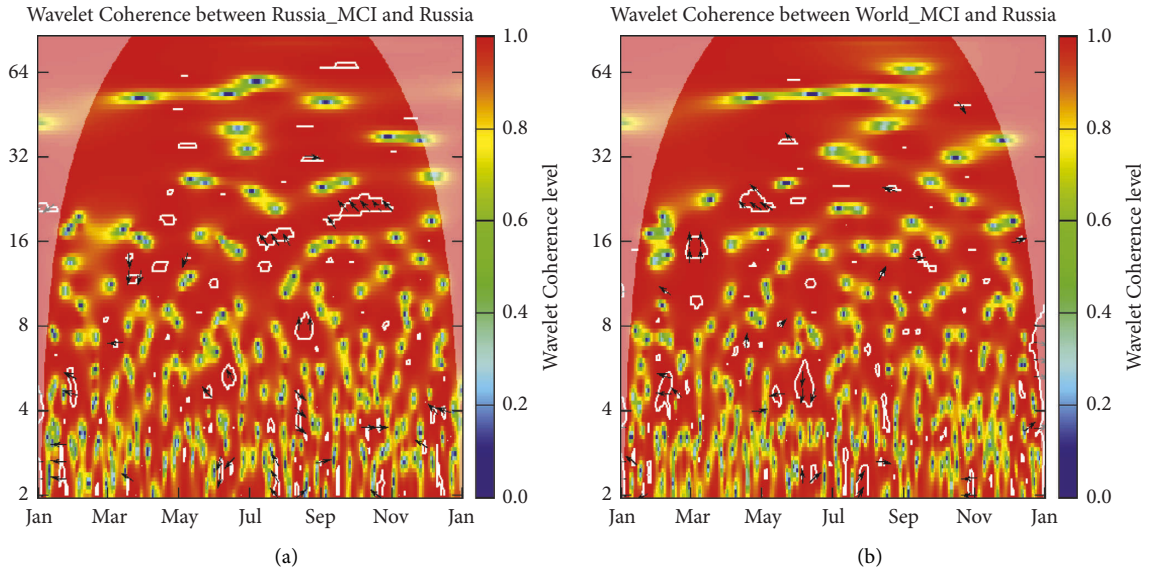

Figure 3: MCI and Russian equities in the initial COVID-19 pandemic year. The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

coverage. This is evidenced by the (↖) and (↘) positioning arrows spotted between August and December 2020 at high frequencies between 2 and 8 daily periodicities. Between the 12 and 16 daily periodicities in September and October 2020, the antiphase positioning arrows imply an inverse connection between local MCI and Indian equities, which may correspond to revisions in policies targeted at containing the spread of the virus and/or the emergence of new variants. Meanwhile, around scale 28–48 daily periodicities, Indian equities led their co-movement with local COVID-19-related media coverage from July through till January 2021. Again, it is unsurprising of this class of equities, as they fall under emerging markets assets.

A careful examination of the co-movement dynamics between the world MCI and Indian equities across the higher frequency bands (2–3 daily periodicities) reveals a leading or driving role of world media coverage of COVID-19-related news. This is seen for March, June, and October 2020. As an emerging market with equities whose dynamics are highly predictable, Indian equities assumed the leading or driving role for its co-movements with world media coverage specifically between 4 and 6 daily periodicities in March, June, and September 2020. The antiphase positioning arrows spotted across medium frequency scales (16–28 daily cycles) in April and May 2020 revealed a negative impact of the COVID-19 pandemic on Indian equities, while the cloud

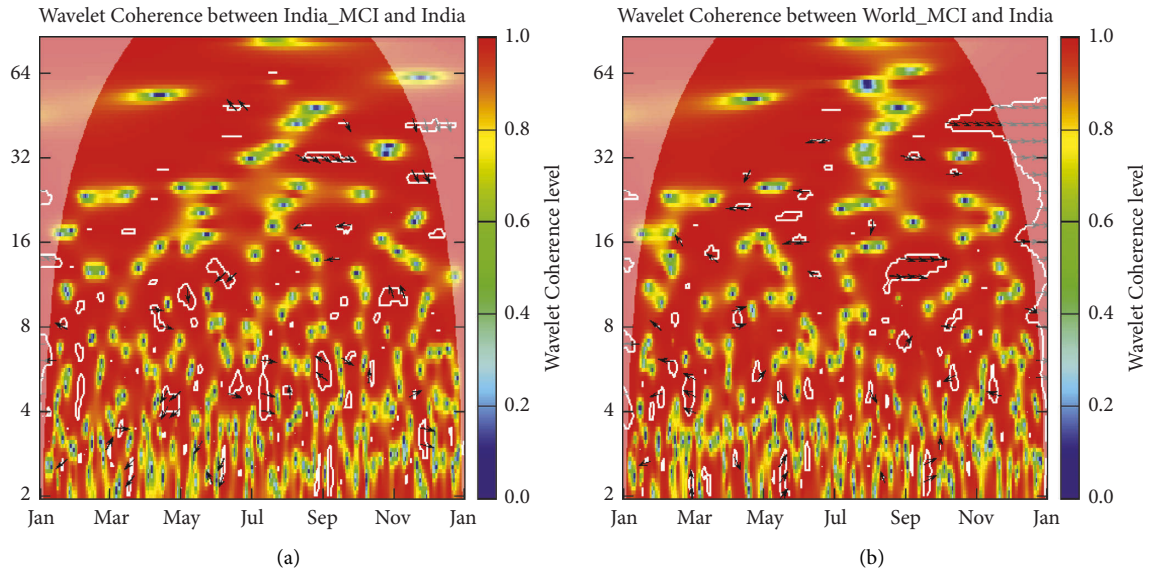

Figure 4: MCI and Indian equities in the initial COVID-19 pandemic year. The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

of positioning arrows spotted between September and October 2020 suggests positive co-movements between Indian equities and world MCI; this persists across high and low-frequency bands (i.e., between 4 and 52 daily periodicities) from November 2020 to January 2021. Thus, as the market gets saturated with global COVID-19 media coverage, fundamental dynamics tend to emerge across the lower frequencies. Thus, COVID-19 shocks hardly reduced Indian equity prices during such periods.

3.1.4. Media Coverage Index and Equities of China in the Initial COVID-19 Outbreak Year. Figure 5 portrays the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Chinese equities in the first outbreak year.

The co-movement dynamics between local media coverage and Chinese equities (panel A of Figure 5) indicate a positive coherence between media coverage and equities from China across high and medium frequencies in January 2020, specifically at 3–14 daily cycles. Between the 2–3 frequency band, in the early days of February 2020 and between 3 and 14 daily cycles in March–June 2020, Chinese equities led their co-movements with COVID-19 media coverage. This is shown by the (↘) and (↖) positioning arrows. The lucrative character of Chinese equities, as a subset of top-emerging market equities, results in these dynamics despite the shocks from the COVID-19 pandemic. This may be a result of their smart and timely measures rolled out to conquer the pandemic, which they were the main source of. Their strategies put in place to curb the pandemic might have outpaced the impact of the shocks from the pandemic through media coverage. Local media coverage is seen to occupy the leading role at 1.5–3 daily cycles in the early days of August 2020, but this was overturned in late (early) August (September) of the year 2020. The antiphase relationships noticeable between November and December 2020 implied a negative impact of COVID-19 shocks on Chinese equities at high frequencies (2–4 daily periodicities). Notwithstanding, Chinese equities outpaced local media coverage at medium frequencies (7–10) daily cycles in December 2020.

The co-movement dynamics between world media coverage and Chinese equities are portrayed in panel B of Figure 5. From the coherence plot, the lead-lag nexus between world MCI and Chinese equities does not differ significantly from that of local MCI and Chinese equities in panel A. The positive impact of media coverage on Chinese equities is revealed at low to medium frequencies (3–14 daily cycles) in January 2020. World MCI takes a lead role in March 2020, when the coronavirus was declared a pandemic by WHO. This persists at high frequencies (2-daily periodicities) in July and October 2020. The cloud of left and up-diagonal (↖) positioning arrows across 14–18 daily scales communicates that Chinese equities drive their co-movements with COVID-19 media coverage. As the year 2020 ends, similar to other BRICS markets, Chinese equities are positively impacted by world media coverage of COVID-19-related news. As indicated by the right-pointing (→) positioning arrows, low, medium, and high-frequency bands, world COVID-19 shocks may pose no detrimental effect on Chinese equities.

3.1.5. Media Coverage Index and Equities of South Africa in the Initial COVID-19 Outbreak Year. Figure 6 portrays the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and South African equities in the first outbreak year.

From panel A of Figure 6, the co-movement dynamics between local media coverage and South African equities are displayed. The positioning arrows at high frequencies (2–3

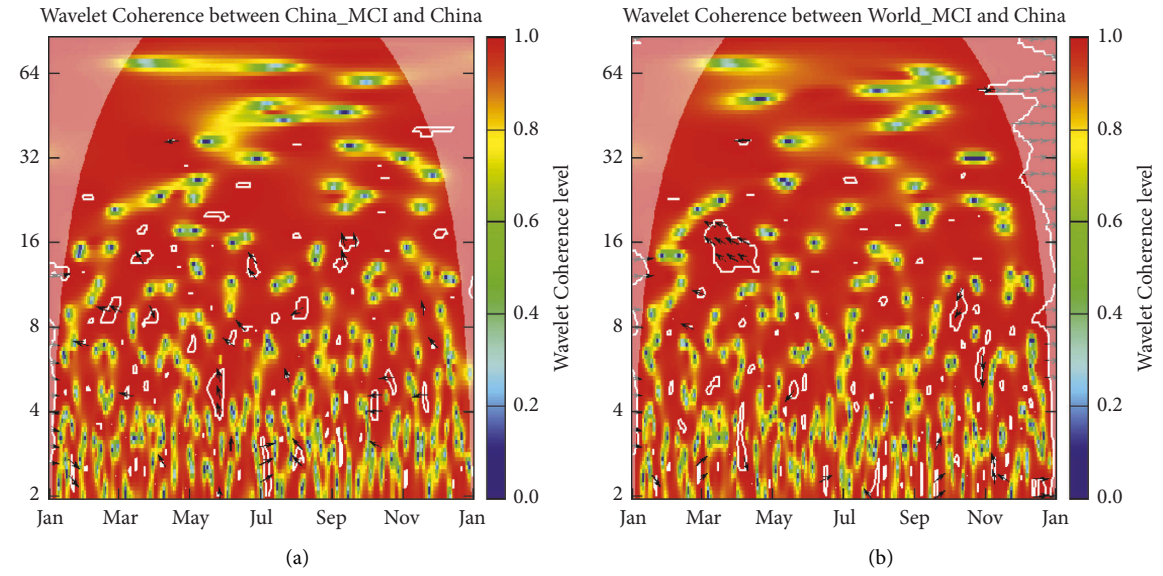

Figure 5: MCI and Chinese equities in the initial COVID-19 pandemic year. The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

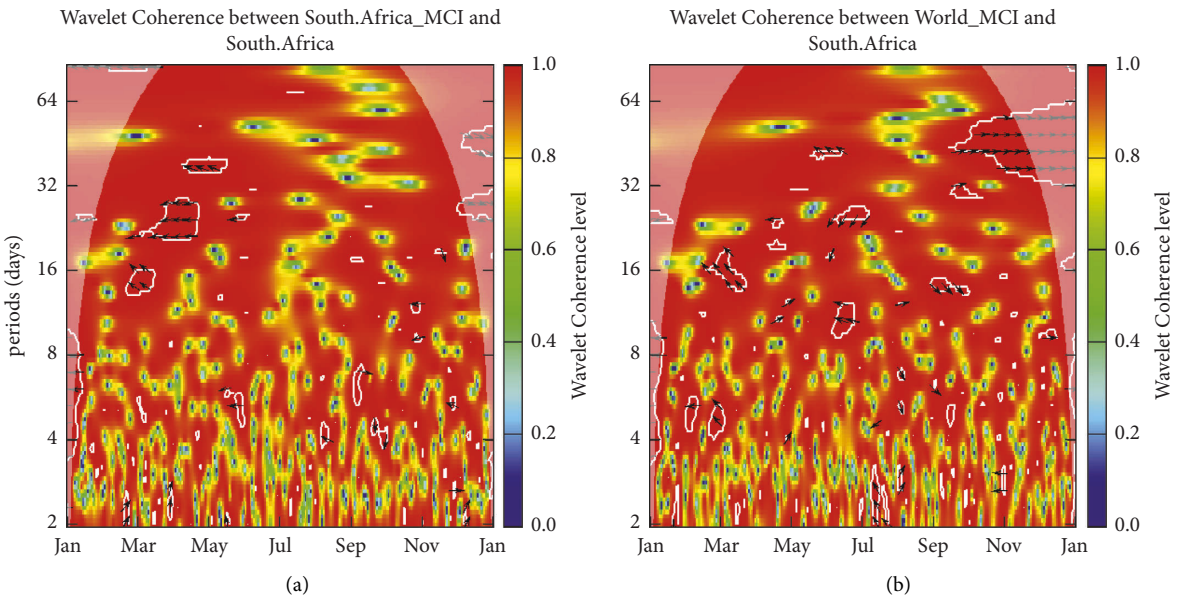

Figure 6: MCI and South African equities in the initial COVID-19 pandemic year. The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

daily periodicities) in the early months (between March and May) of the pandemic shows that media coverage influenced the equity market dynamics in South Africa. This persisted across 20–32 daily cycles within the same period. However, across the 12–16 and beyond the 32-daily cycles, South African equities led their co-movements with local media coverage. South Africa is a member of the African continent, which was the last to record a case of COVID-19. Yet, local media coverage of the pandemic had a detrimental impact on their equities. However, being a part of the top emerging markets globally and the lead market for the African continent, its lucrative character made it overturn the negative impact posed by COVID-19 shocks in the first few months. Indicatively, despite interspersed phase difference arrows, South African equities take on the driving role after December 2020, although this may not be captured by the COI.

Turning to the world media coverage and South African equities' co-movement dynamics, which are revealed by the coherence plot in panel B of Figure 6, similar dynamics from the local MCI hold for the world MCI. However, the leading role of South African equities is clearly shown in this case.

The mix of positioning arrows at high frequencies (2–4 daily cycles) partly communicates the hasty market events exhibited by international market participants in the presence of COVID-19 safety protocols and containment measures. Aside from the leading role of world MCI across 12–14 and 24–26 daily periodicities between May and July 2020, the remaining positioning arrows largely communicate the lead position of South African equities at medium frequencies from March to October 2020. Between 32 and 64 daily cycles, the right-pointing (→) positioning arrows indicate a positive relationship between world media coverage, as a proxy for COVID-19 shocks, and South African equities. This observation is consistent among other BRICS economies and, hence, unsurprising.

3.2. Media Coverage and BRICS Equities in the "New Normal" (2021–2022). We now analyze each BRICS equity market's co-movement dynamics with local and global media coverage in the "new normal" era. We expect that dynamics in various BRICS equity markets will bounce back to normal after they may become saturated with COVID-19 media coverage, either local or global. The individual BRICS markets are analyzed as follows.

3.2.1. Media Coverage Index and Equities of Brazil in the "New Normal". Figure 7 reveals the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Brazilian equities in the new normal era.

As depicted in Figure 7 A, in the "new normal" era, local media coverage tends to generally drive Brazilian equities across high frequencies (2–8 daily periodicities). Positioning arrows are more of (↙) and (↗), suggesting that the dynamics in the Brazilian equity market are influenced by local media coverage of COVID-19-related news. As recovery tends to be slower, market participants carefully monitor the pandemic through news outlets, and this may influence the pricing of stocks. At low frequencies (around 100 daily cycles) in the early parts of 2021, Brazilian equities took the lead position, but this has been inconsistent in subsequent periods.

When the world media coverage is considered (panel B of Figure 7), we spot Brazilian equities in the lead position in the early days of 2021 between the 16–32 frequency band and in the latter part of 2021 around 8–12 daily cycles. Except for these periods, all other positioning arrows suggest that world media coverage drives Brazilian equities. An inconsistent positive nexus between world MCI and Brazilian equities are found around 6-daily periodicities in the early days of 2022. It is worth mentioning that the resulting positioning arrows for the "new normal" era show the complex behavior of financial markets and the power of social media coverage.

3.2.2. Media Coverage Index and Equities of Russia in the "New Normal". Figure 8 displays the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Russian equities in the "new normal" era.

In the "new normal," the positioning arrows from the coherence plot between local media coverage and Russian equities show a split in the lead-lag positions. Local MCI leads Russian equities at intermittent wavelet scales in the first half of 2021. Across the frequency bands 16–20 and approximately 64–72 of mid-2021, Russian equities lead their relations with local MCI. This is also envisaged at a high-frequency band (2–3 daily cycles) in the early part of 2022. Meanwhile, Russian equities take a lag position around 12-daily cycles.

Turning to the world MCI, Russian equities responded negatively to world COVID-19 media coverage in the first quarter of 2021. In the second quarter of 2021, Russian equities (world MCI) lagged (led) world COVID-19 media coverage (Russian equities). In the "new normal" era, indications of the leading role of Russian equities manifest in the 16–32 frequency band in the third quarter of 2021. After this period, the leading role of world MCI is found dominant across medium- and low-frequency bands in 2021-ending and the beginning of 2022.

3.2.3. Media Coverage Index and Equities of India in the "New Normal". Figure 9 depicts the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Indian equities in the "new normal" era.

Distinct from Brazilian and Russian equities, Indian equities generally drive local MCI across different frequency bands in the "new normal" era, as depicted by Figure 9's panel A. This is more glaring in the mid- and late-2021 period in the medium- and low-frequency bands. Across high frequencies (2–3 daily cycles) around the second quarter of 2021 and late 2021, right-pointing (→) positioning arrows indicate positive co-movements between local MCI and Indian equities. Meanwhile, local MCI led Indian equities between the 8–16 frequency band in late 2021.

In terms of world MCI, the coherence plot (panel B of Figure 9) shows mixed co-movement patterns between media coverage and Indian equities. However, the general observation points to some world MCI-led co-movements or negative co-movements in 2021, indicating the fact that the global impact of the COVID-19 pandemic is yet to fully materialize among some economies. However, across low frequencies (above 64 daily cycles), Indian equities lead world MCI, suggesting that approaching the long-term of the pandemic, Indian equities are likely to instead drive world media coverage. This is also noticeable across the 3–5 frequency band in the early part of 2022.

3.2.4. Media Coverage Index and Equities of China in the "New Normal". Figure 10 shows the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and Chinese equities in the "new normal" era.

The mixed coherence phase difference arrows found for other BRICS markets are no different from China. From panel A of Figure 10, we find that the coherence between local media coverage and Chinese equities yields interspersed positioning arrows in high and medium frequencies,

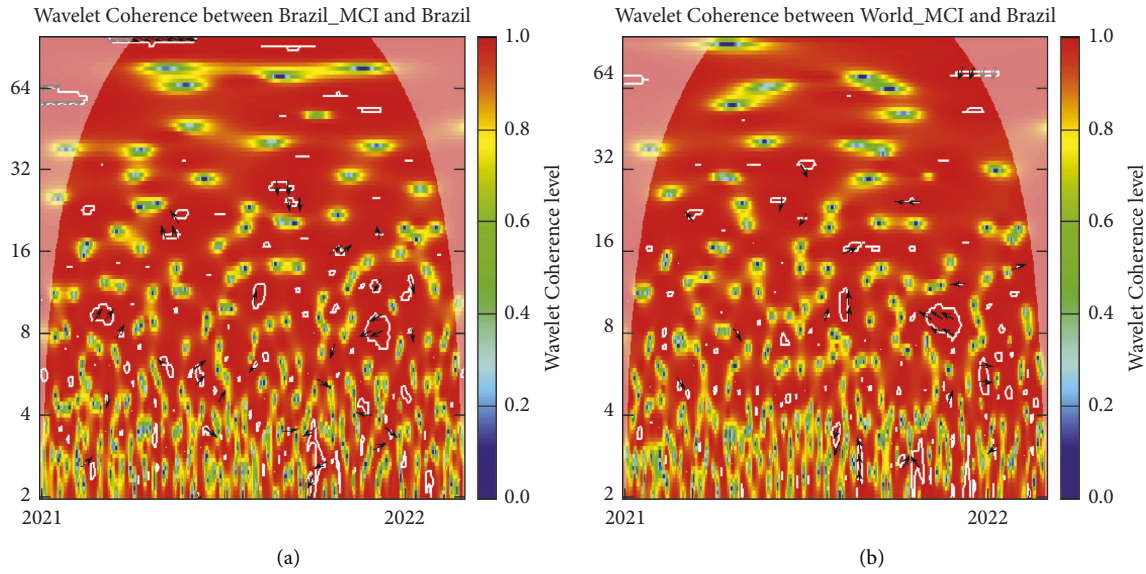

Figure 7: MCI and Brazilian equities in "new normal." The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

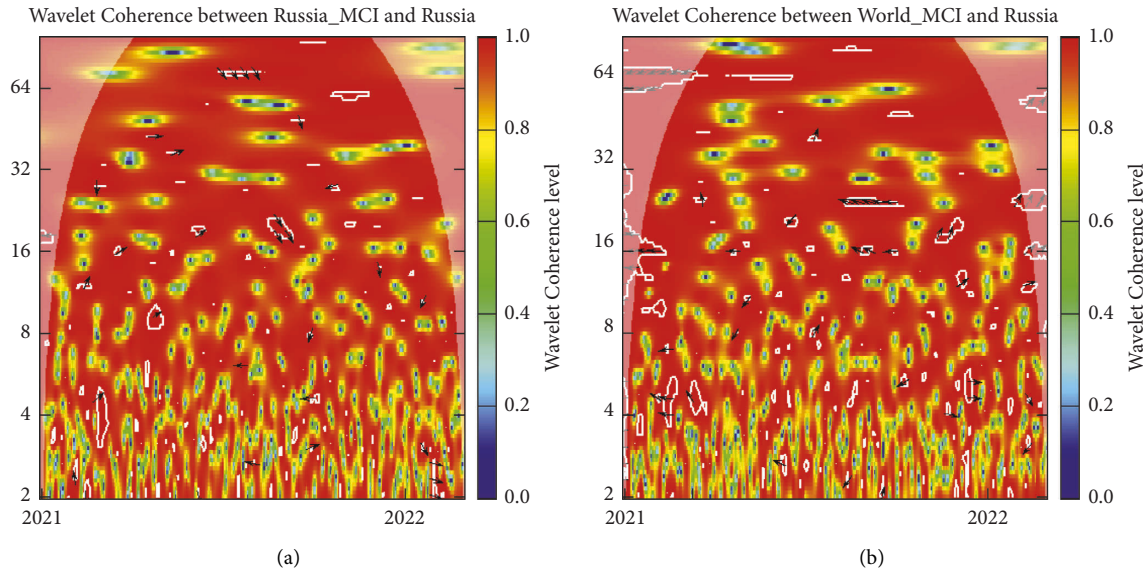

Figure 8: MCI and Russian equities in "new normal." The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

revealing a mix of lead-lag relationships, particularly across the 2–32 frequency band. Thus, it is not clear which of the series consistently leads or lags the other. The lead-lag dynamics are clear at low frequencies (beyond 64 daily periodicities). Across this period in 2021, the leading role of local media coverage of COVID-19 is noticeable.

Whilst Chinese equities fail to consistently drive local media coverage in the "new normal" era, we find that they stand a chance of driving world media coverage in the long term. This is evidenced by the (↘) positioning arrows found between the 32–64 daily cycles in late (early) 2021 (2022). This was also observed during the weekly scale (8-day periodicities) in mid-2021. Whilst Chinese equities were leading world MCI in the first quarter of 2021, across the 3–5 daily frequency band, the co-movements were rather negative nearing the last quarter of 2022 around the same frequency band and the medium frequency band (28–32 daily cycles in mid-2021), as shown by the (←) positioning arrows. These observations reiterate the financial market complexities introduced by the COVID-19 pandemic.

3.2.5. Media Coverage Index and Equities of South Africa in the "New Normal". Figure 11 reveals the wavelet coherence plots for the co-movements between the COVID-19 media coverage index and South African equities in the "new normal" era.

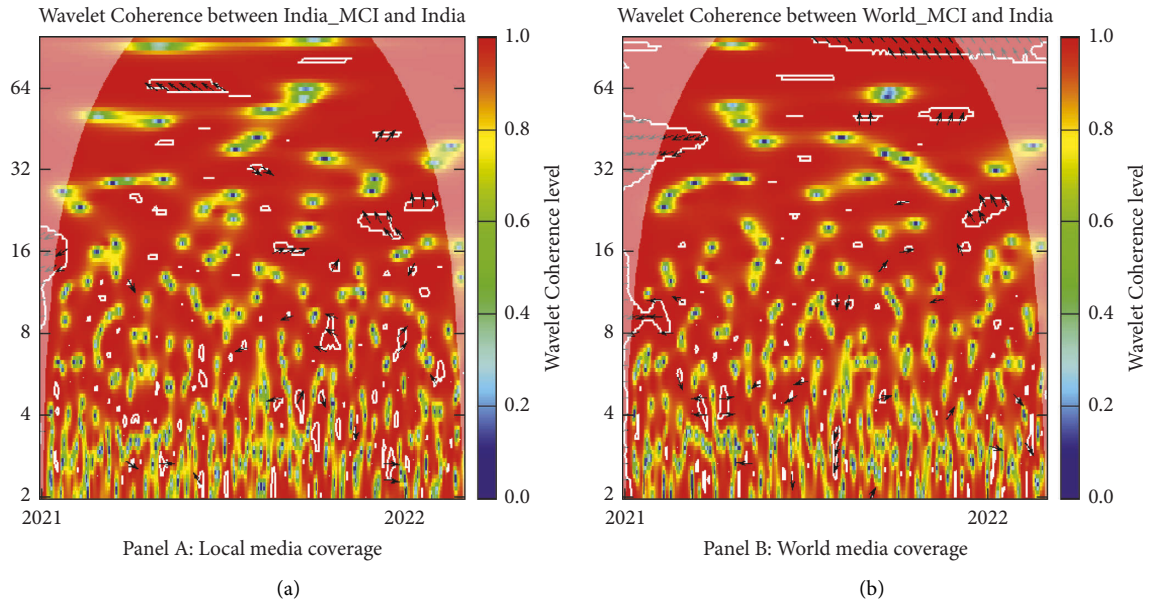

FIGURE 9: MCI and Indian equities in "new normal." The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

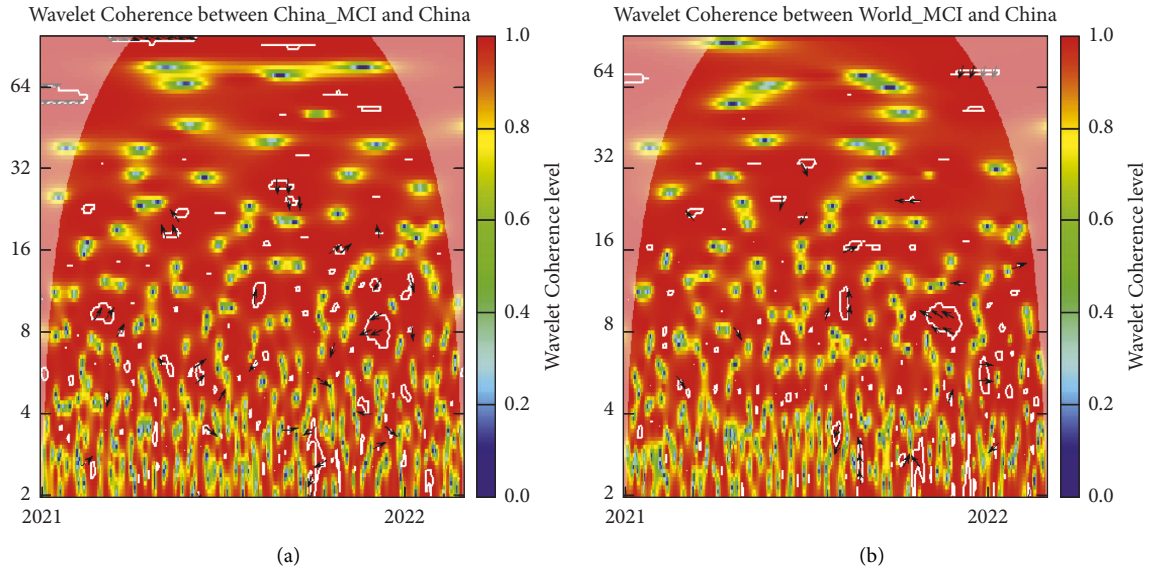

FIGURE 10: MCI and Chinese equities in "new normal". The values on the x axis show the dates, and the values on the y axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

In the case of South Africa, we find that the coherence between local media coverage and South African equities (see panel A of Figure 11) was driven by local media coverage in the first quarter of 2021 between the 2–4 daily frequency band. Around the mid-2021, across the same frequency band, South African equities assumed the lead position. This was also noticeable between the 4–6 daily periodicities. These were followed by downward positioning arrows (↓), signifying that South African equities led local media coverage by $\pi/2$ at the 3-daily frequency band. With (↗), (↙) and (↑) positioning arrows, the leading role of local media coverage was noticeable across the medium frequency band (8–32 daily cycles) in the "new normal" era, particularly in, the 2021 and early 2022. Across low-frequency band (58–80 daily cycles), from the middle to the end of 2021, we find left-pointing (←) positioning arrows, showing negative co-movements between local media coverage and South African equities.

When we incorporate world media coverage, we find a negative and world MCI-driven impact of media coverage on South African equities at the high-frequency band (2-daily cycles) in the early period of 2021. In the last quarter of

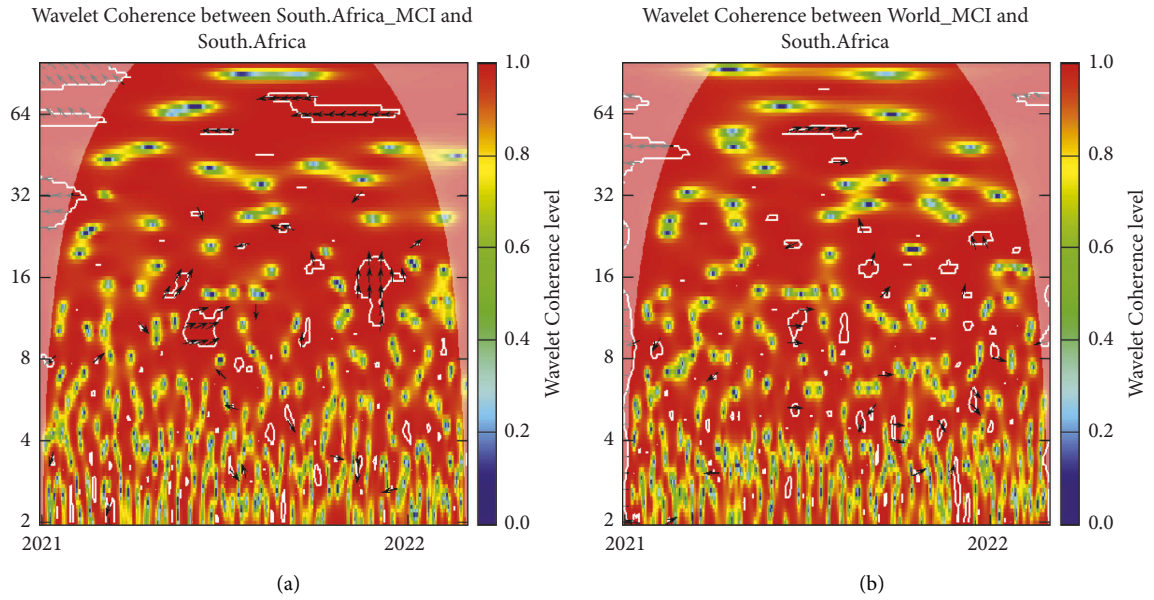

Figure 11: MCI and South African equities in "new normal." The values on the *x* axis show the dates, and the values on the *y* axis show the frequency (in days). (a) Panel A: Local media coverage. (b) Panel B: World media coverage.

2021, across the 4–8 frequency band, South African equities drive their co-movement with world media coverage. This is similar to the observation in respect of local media coverage. However, in the "new normal," across the medium frequency band, South African equities show a positive response to world media coverage in mid-2021. South African equities then assume a lagging role nearing the 54-daily frequency band in mid-2021, with a slight potential of leading world media coverage around the 28-daily frequency band in early 2022.

Similar to all BRICS markets, the "new normal" reveals a much more complex interrelation and lead-lag dynamics between media coverage indices, be it local or world, and equity markets.

3.3. Results' Implications. Our findings reveal some practical intuitions for market participants and policymakers. First, our findings indicate that COVID-19-related shocks, proxied by media coverage indices, co-move with equity markets not only in the time domain but also in the frequency domain. The significant co-movement in the time-frequency space indicates that when formulating policy at a given period, the frequency domain, which represents trading horizons in a given timeframe, needs to be incorporated. This is to ensure that significant market dynamics between COVID-19 shocks and financial markets are rightly synchronized in the process of crafting policy actions. Our observation of significant time and frequency domain co-movements between media coverage and equities corroborates the existing literature that reveals time- and frequency-dependent dynamics between media coverage and financial assets [25].

Second, to market participants, we note that given the length of time the pandemic has lasted, media coverage serves as a proxy for public mood and/or investor sentiments at the societal level, thus extending the literature strand on analyzing the capital markets' complexities with media data [2, 3]. Our findings evidence the complexities in the BRICS equity markets. This is shown by the mixed and inconsistent co-movement dynamics between media coverage and each of the BRICS equities at high frequencies (up to weekly trading cycles). Impliedly, during crisis periods, investors (and regulators alike) should be wary of short-lived and inconsistent market dynamics that may render decisions ineffective.

Third, comparing the market dynamics in the initial COVID-19 pandemic year to those in the "new normal" era, for all BRICS markets, we identify significant changes in the co-movements between how local and world media coverage indices interact with emerging market equities. Aside from paving the way for additional research on this subject, the disparities in market dynamics suggest that timely rebalancing of international portfolios is necessary given that the new norm brings to investors more complex dynamics and intense effects of COVID-19 shocks on financial assets. BRICS equities are part of the top emerging markets equities that offer substantial risk-reduction benefits to investors from developed markets [5–7]. Therefore, as the "new normal" period has caused a change in investor sentiments, a careful selection of emerging market equities, particularly highly integrated ones like BRICS, is recommended to reduce overall portfolio risks.

Lastly, our findings underscore the significance of both global and local media coverage in determining equity markets' price-generating dynamics. However, the complex co-movement dynamics between world media coverage and

BRICS equities stress the pivotal role of global factors in driving financial markets [26]. Indicatively, we note that when market participants focus solely on local media coverage, some decisions may be compromised given that when world media coverage is incorporated, the dynamics in equity markets change significantly. Hence, as markets have evolved to the "new normal," investors, policymakers, and regulators should not uphold local sentiment factors more than global factors.

4. Conclusions

We examined the time-frequency co-movement patterns between COVID-19 media coverage and equities from the BRICS market bloc, which contains Brazil, Russia, India, China, and South Africa. We employed daily equity indices and both world media coverage indices (WMCI) and local media coverage indices (LMCI). Our datasets span between January 2020 and March 2022. Under the wavelet coherence methodology, we comparatively assessed the co-movement dynamics between LMCI and WMCI, and each of the BRICS equity markets.

Due to the high integration between BRICS markets, we found that the co-movement patterns between media coverage and each of the BRICS equities are largely comparable. In the initial year of the COVID-19 outbreak, our results indicated that BRICS markets provided some shield against COVID-19 shocks, proxied by both local and world media coverage across medium and low frequencies, which largely corresponds to monthly and quarterly trading periods. In the "new normal" era, our findings revealed more complex co-movement dynamics between media coverage and BRICS equities. In particular, we find that global COVID-19 media coverage drives and poses high risks to emerging market equities across medium and low frequencies.

From our findings, we conclude that focusing on local sentiment factors alone will insufficiently explain financial markets' complexities. As a result, the essence of synchronizing local and global sentiment factors is pivotal to portfolio management in the "new normal" era. Policymakers should not disregard global factors when devising new measures for economic and trading operations in the "new normal" era. In addition to a timely rebalancing of portfolios, investors should carefully select assets from emerging markets or other market blocs that may be highly integrated.

Future works should examine the role of world media coverage in other advanced economies or market blocs. In addition, any asymmetric and nonlinear dynamics could be investigated, as well as a distinction between the direct and indirect impact of the COVID-19 pandemic. This suggestion comes from an anonymous referee.

Data Availability

All data on BRICS equities were sourced from the Bloomberg database. Media coverage data were provided by RavenPack.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] P. Quinsee, "Global equity views Asset class views," 2021, https://am.jpmorgan.com/us/en/asset-management/adv/insights/portfolio-insights/asset-class-views/equity/.

[2] J. Bukovina, "Social media big data and capital markets - an overview," *Journal of Behavioral and Experimental Finance*, vol. 11, pp. 18–26, 2016.

[3] M. L. Tseng, "Using social media and qualitative and quantitative information scales to benchmark corporate sustainability," *Journal of Cleaner Production*, vol. 142, pp. 727–738, 2017.

[4] L. R. Gavish, M. Qadan, and J. Yagil, "Net buyers of attention-grabbing stocks? Who exactly are they?" *The Journal of Behavioral Finance*, vol. 22, no. 1, pp. 26–45, 2021.

[5] B. G. Buchanan, P. C. English, and R. Gordon, "Emerging market benefits, investability and the rule of law," *Emerging Markets Review*, vol. 12, no. 1, pp. 47–60, 2011.

[6] W. Mensi, S. Hammoudeh, and S. H. Kang, "Risk spillovers and portfolio management between developed and BRICS stock markets," *The North American Journal of Economics and Finance*, vol. 41, pp. 133–155, 2017.

[7] P. Panda, S. Vasudevan, and B. Panda, "Dynamic connectedness among BRICS and major countries stock markets," *Journal of Public Affairs*, vol. 21, no. 3, 2021.

[8] E. A. Nunoo, P. O. Junior, A. M. Adam, and A. Bossman, "Assessing the safe haven properties of oil in African stock markets amid the COVID-19 pandemic: a quantile regression analysis," *Quantitative Finance and Economics*, vol. 6, no. 2, pp. 244–269, 2022.

[9] M. Qadan and M. Jacob, "The value premium and investors' appetite for risk," *International Review of Economics & Finance*, vol. 82, 2022.

[10] M. Qadan and M. Zoua'bi, "Financial attention and the demand for information," *Journal of Behavioral and Experimental Economics*, vol. 82, Article ID 101450, 2019.

[11] A. S. Kumar and S. R. Padakandla, "Testing the safe-haven properties of gold and bitcoin in the backdrop of COVID-19: a wavelet quantile correlation approach," *Finance Research Letters*, vol. 47, Article ID 102707, 2022.

[12] M. Arif, M. A. Naeem, M. Hasan, M. S. Alawi, and F. T. Hesary, "Pandemic crisis versus global financial crisis: are Islamic stocks a safe-haven for G7 markets ?" *Economic Research-Ekonomska Istraživanja*, vol. 35, pp. 1–21, 2021.

[13] E. C. M. Hui and K. K. K. Chan, "How does Covid-19 affect global equity markets?" *Financial Innovation*, vol. 8, no. 1, pp. 25–19, 2022.

[14] M. Youssef, K. Mokni, and A. N. Ajmi, "Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: does economic policy uncertainty matter?" *Financial Innovation*, vol. 7, no. 1, pp. 13–27, 2021.

[15] F. Zeren and A. Hizarci, "The impact of COVID-19 coronavirus on stock markets: evidence from selected countries,"

Muhasebe ve Finans İncelemeleri Dergisi, vol. 3, no. 1, pp. 78–84, 2020.

[16] D. Zhang, M. Hu, and Q. Ji, "Financial markets under the global pandemic of COVID-19," *Finance Research Letters*, vol. 36, Article ID 101528, 2020.

[17] S. M. Hashmi, B. H. Chang, and L. Rong, "Asymmetric effect of COVID-19 pandemic on E7 stock indices: evidence from quantile-on-quantile regression approach," *Research in International Business and Finance*, vol. 58, Article ID 101485, 2021.

[18] C. Torrence and G. P. Compo, "A practical guide to wavelet analysis," *Bulletin of the American Meteorological Society*, vol. 79, no. 1, pp. 61–78, 1998.

[19] C. Torrence and P. J. Webster, "Interdecadal changes in the ENSO-Monsoon system," *Journal of Climate*, vol. 12, no. 8, pp. 2679–2690, 1999.

[20] A. Bossman, A. M. Adam, P. Owusu Junior, and S. K. Agyei, "Assessing interdependence and contagion effects on the bond yield and stock returns nexus in Sub-Saharan Africa: evidence from wavelet analysis," *Scientific African*, vol. 16, 2022.

[21] A. Rua and L. C. Nunes, "International comovement of stock market returns: a wavelet analysis," *Journal of Empirical Finance*, vol. 16, no. 4, pp. 632–639, 2009.

[22] J. Morlet, G. Arens, E. Fourgeau, and D. Glard, "Wave propagation and sampling theory – Part I: complex signal and scattering in multilayered media," *Geophysics*, vol. 47, no. 2, pp. 203–221, 1982.

[23] J. Morlet, G. Arens, E. Fourgeau, and D. Giard, "Wave propagation and sampling theory – Part II: sampling theory and complex waves," *Geophysics*, vol. 47, no. 2, pp. 222–236, 1982.

[24] P. Goupillaud, A. Grossmann, and J. Morlet, "Cycle-octave and related transforms in seismic signal analysis," *Geoexploration*, vol. 23, no. 1, pp. 85–102, 1984.

[25] Z. Umar, M. Gubareva, and T. Sokolova, "The impact of the Covid-19 related media coverage upon the five major developing markets," *PLoS One*, vol. 16, no. 7, p. 28, 2021.

[26] C. D. Gaina and D. Philippas, "Local versus global factors weighing on stock market returns during the COVID-19 pandemic," *Finance Research Letters*, vol. 46, Article ID 102270, 2022.

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Review Article

A Bibliometric Analysis on Agent-Based Models in Finance: Identification of Community Clusters and Future Research Trends

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Agent-based models are computational approaches used to reproduce the interactions between economic agents. These models are widely applied in many contexts to get deeper understanding about agents' behaviors within complex systems. In this paper, we provide a bibliometric analysis about agent-based models in finance and, considering bibliographic coupling, we identify the presence of two distinct clusters of research communities, i.e., financial economics and econophysics. Cluster-specific thematic analyses are conducted to understand if the two communities are characterized by different emerging and motor topics. By highlighting several differences in the clusters, we also show the two research communities specialized in different specific topics.

1. Introduction

Since the beginning of the 1990s, agent-based models have been an emerging topic in economics literature. In finance, agent-based models have been used to reproduce the well-known stylized facts of financial markets, such as heavy tails, volatility clustering, and long memory (see Cont [1]). Economic models usually have a representative agent who is perfectly rational and uses the principle of utility maximization to act. In contrast, agent-based models, which originated in statistical physics, allow us to go far beyond the assumptions of classical economics.

Despite the presence of some review articles on the topic (e.g., see Chakraborti et al. [2], Chen et al. [3], Huang [4]), we note that these studies have been conducted with the adoption of qualitative approaches. In contrast to classical qualitative reviews, modern and more appropriate quantitative techniques exist and can be successfully used to conduct a systematic literature analysis.

In this sense, bibliometric studies provide systematic, transparent, and reproducible reviews conducted through statistical measurement of science (Aria and Cuccurullo [5]). The aim is to deeper understand the authors' network structures, i.e., the analysis of scholars' communities, and to identify trending and declining topics (e.g., see Aria et al. [6]) as well as the determination of journal performances. Despite a few recent attempts (e.g., Paltrinieri et al. [7] and Khan et al. [8]), the use of *science mapping* approaches for literature review in finance is still poorly explored.

Considering the qualitative analyses on the topic, it emerges that the most important contributions have been published in econophysics and economics journals. Therefore, it is natural to suppose that two clusters of research communities exist when studying the literature on agent-based finance models. If two research communities exist, it is interesting to study if they are specialized in specific topics and which these topics are. To the best of our knowledge, this aspect has never been investigated by previous studies concerning agent-based modeling in finance.

Therefore, the paper aims to contribute to previous literature in two ways. First, by using the R package bibliometric developed by Aria and Cuccurullo [5], we aim to

fill the gap related to quantitative literature reviews by providing the first bibliometric analysis for agent-based models in finance. Hence, the paper aims to identify emerging and decreasing topics in financial agent-based modeling. Second, we explore the differences in the topics among distinct research communities through cluster-based thematic maps, identified by performing a coupling analysis (Kessler [9]).

Our main findings show the presence of two main clusters of scholars' communities that are identified based on the journals in which the papers are published. As the main result, we demonstrate that the econophysics research community, represented by the articles published in physical sciences journals, clearly differentiates from the economics and finance community, represented by the articles published in finance-related journals. In particular, asset pricing and trading give motor topics for the econophysics community. In contrast, those of the economics community are related to financial crises and the interaction of finance with macroeconomic fluctuations. Furthermore, our results highlight that the study of market microstructure is an emerging topic for the econophysics community, while asset pricing is becoming more popular for economics. These findings can serve as a tool to orientate researchers in identifying the most suitable journal—more precisely, its area, i.e., either econophysics or financial economics—for their last research on the topic.

The paper is structured as follows. Section 2 provides a brief overview of the most relevant papers in financial agent-based modeling, while Section 3 discusses the collected data and main descriptive results obtained with quantitative techniques. A detailed analysis of the most influential sources is provided as well. Section 4 demonstrates the presence of clusters of journals with a coupling algorithm. Then, Section 5 provides a detailed within cluster analysis, showing cluster-specific thematic maps as well as the analysis of trend topics. In the end, a discussion of the results and concluding remarks are presented.

2. Brief Overview about Agent-Based Modeling in Finance

The works have been extended in three representative areas:

(i) Multiagent models for modeling orders

(ii) Agent-based modeling for wealth distributions: Kinetic theory models

(iii) Agent-based modeling based on game theory

In economics, agent-based models are considered a competitor of standard dynamic stochastic general equilibrium (DSGE). Fagiolo and Roventini [10] present an engaging survey about the contribution of agent-based models in economics.

According to Fagiolo et al. [11], in finance, the agent-based models allow for more descriptive richness, as they describe ecologies of agents, locally interacting through nonobvious network structures, learning to use incomplete information, and competing within imperfect markets.

Until the beginning of this century, the agent models incorporated from behavioral finance were built with agents that can exchange actions according to exogenously defined utility functions that reflect their preferences and risk aversion. Although they have achieved some of their goals, they suffer from many drawbacks: first, they are very complex, and it can be a challenging task to identify the roles of their many parameters and the types of dependencies between them; second, the chosen utility functions do not necessarily reflect what is observed in the mechanisms of a financial market.

The first work simulating a financial market is carried out by Stigler [12], where the author studies the effect of the SEC regulations on the American market using empirical data from 1920 to 1950. In 2008, Slanina [13] implements the model developed by Stigler and discovers that it can reproduce the behavior of heavy tails, although with an α far from the empirical one, as expected due to the restrictions of the original model.

Garman [14] makes an early study of a double auction market with a point of view that does not ignore the time structure and also defines the order flows. The main contribution of this work is to provide for the first time an empirical study of the market microstructure. In both models, orders arrive at the market randomly within price ranges. The agents do not observe the market; therefore, their strategy does not depend on it, so these models are considered *zero-intelligence* models. However, this concept is attributed to Gode and Sunder [15] to explain the blind behavior of operators who randomly send orders to the market.

These authors study two types of market operators: with restrictions and without them. The authors' goal was to show that double auction markets exhibit intrinsic allocation efficiency (the ratio of the total profit earned by traders divided by the maximum possible profit) even with zero-intelligence traders. An interesting fact is that the price series resulting from the actions of zero-intelligence traders are much more volatile than those obtained from constrained traders. Cont and Bouchaud [16] introduce noise traders that follow herd behavior. The idea is also used by Raberto et al. [17]. Lux and Marchesi [18] propose an agent model in which traders interact with each other. In all these models, the price variation depends on the balance between the buy and sell orders throughout the development of the model.

An important step is when the models consider the limit orders that are sent to the market but are not executed. Chiarella and Lori [19] build an agent model in which the operators send the orders to the market according to the types established by Lux and Marchesi [18], that is, chartists, fundamentalists, and "noise" traders. Orders are stored in an order book.

However, the most important step is taken when the rational agents that make up the models in economics tend to disappear and be replaced by the notion of flows: the orders are no longer sent by an agent that follows a strategic behavior, but are seen as an arriving flow, whose properties must be determined by empirical observations of market mechanisms. Therefore, order modeling requires more

stylized facts. Market orders, limit orders, arrival time, and execution are studied. Bouchaud et al. [20] and Potters and Bouchaud [21] provide the statistical characteristics of the order book itself and are the basis for zero-intelligence models, in which stylized facts are expected to be reproduced by the properties of the order flows and their structure. Chalet and Stinchcombe [22] propose an order flow model where limit orders are stored in a mechanism that removes them if not executed.

Since the 1990s, physicists have made fascinating contributions to this research line. Bak et al. [23] developed the first physics-inspired model. The author considers a market with N noise traders capable of exchanging one stock at a time. As the author points out, the simulation process is based on a physical reaction-diffusion model of the type.

In the model, no broad tails are observed in the returns, but the typical decay of the distribution's tails seems to be visible. The main drawback of the model is that moving orders are unrealistic for modeling an order book. Since it does not reproduce any known financial exchange mechanism, it cannot be the basis of a more general model. However, the scientific community seems to agree that the basic model is fascinating due to its simplicity. Maslov [24] maintains the structure of Bak et al. [23], but introduces some more realistic assumptions of market evolution. First, the limit orders are submitted and stored in the model, without moving. Second, limit orders are posted around the best quotes. Third, market orders are submitted to trigger trades. Numerical simulations show that this model exhibits non-Gaussian heavy-tailed distributions of returns. However, the Hurst exponent of the price series is still $H = 0.25$ in this model. This model introduces interesting innovations in order book simulation: an order book with limit (fixed) orders, market orders, and the need to cancel orders, waiting too long in the order book. These features are of paramount importance in any following order book model.

Subsequently, Chalet and Stinchcombe [22] continued the work of Bak et al. [23] and Maslov [24] and developed the analogy between the dynamics of an order book and an infinite one-dimensional grid, where the particles of two types (ask and bid) are subject to three types of events: deposition (limit orders), annihilation (market orders), and evaporation (cancelation). It appears that the series of price returns simulated with this model exhibits a Hurst exponent of 0.25 for short time scales, and that it tends to $H = 0.5$ for longer time scales.

These three models can successively isolate the essential mechanisms to be used when simulating a realistic market: order is the smallest unit; sending order is the time dimension; the presentation of market orders and the cancelation of orders are taken into account. On the one hand, one can try to describe these mechanisms using a reduced number of parameters, using a Poisson process with constant rates for order flows and constant volumes. On the other hand, one can try to fit more complex empirical distributions to market data without analytical concerns. Mike and Farmer [25] develop a model that proposes a more advanced calibration with market data when placing and canceling orders. With regard to volume and time of arrival and execution, the assumptions of the previous models are maintained, with no distinction being made between market orders and limit orders.

The results of this empirical model are quite satisfactory concerning the yield and spread distribution. As for the drawbacks, we can mention the instability of the order book. Simulations using empirical data show that situations can occur that empty the order book due to extreme market events. Another drawback is that the model does not take volatility clusters into account. In this line, Gu and Zhou [26] propose some model variations. Another major drawback of the model is how the order signs are simulated. As the authors pointed out, using an exogenous fractional Brownian motion leads to correlated price returns, which contradicts the stylized empirical facts.

In all the models discussed above, the order flows as independent processes. Under certain modeling constraints, the order books can be viewed as a Markov chain. In any case, even if the process is empirically detailed and nontrivial, they work with the assumption that the orders are independent and identically distributed. This very restrictive (and false) hypothesis is similar to the representative agent hypothesis in economics: commands that are sent successively and independently, and we can expect nothing more than regular behavior. Following the work of economists like Kirman [27–30], it is necessary to translate the heterogeneous property of markets into agent-based models. Agents are not identical or independent.

The model presented by Cont and Bouchaud [16] considers a market with N agents trading stock with a price. The idea is to model the diffusion of information between agents by randomly linking their demand through groups. Therefore, this simple model exhibits thick tails in the distribution of returns, with decay reasonably similar to that of the empirical data. Therefore, the authors show that taking into account a naive communication mechanism between agents (herd behavior) can move the model away from Gaussian convergence and produce nontrivial forms of return distributions.

Lux and Marchesi [18] proposed a model very much in line with agent-based models in behavioral finance, but where business rules are kept simple enough that they can be identified with more realistic agents' behavior. This model considers a market with N agents that can be part of two different groups of traders: one group of traders are "fundamentalists," who share an exogenous idea of the value of the current price, and other traders are "chartists" (or trend followers), who make assumptions about the price evolution based on the observed trend (moving average). However, the number of parameters involved and the complicated transition rules between agents make the clear identification of the sources of the phenomena and the calibration to market data complex and intractable.

3. Data Collection and Research Questions

We collect the database on the basis of a query to the Web of Science (WoS) website on January 7, 2022. The WoS database is used in many bibliometric analysis because of its

large coverage of sources: more than 20000 journals, conference proceedings, books, and review articles.

We searched for all the documents related to the topic agent-based model, by using the following query: "Agent-based model*" AND "Finance" OR "Financial market*" OR "Stock market*." The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) scheme (Liberati et al. [31]) was used for the selection process. We considered only papers written in English, and we limited our study only to articles and reviews published between 1992 and 2021, obtaining 1302 entries.

All the analyses shown in this paper have been performed with the open-source R package bibliometric (Aria and Cuccurullo [5]). Table 1 shows the main statistics of the entire collection.

The average number of published papers is about 42 per year. The number of publication shows a positive trend, characterized by an annual growth rate equal to 17.78% (Figure 1).

Figure 1 shows that the scientific interest in agent-based modeling raised especially after the financial crisis. Indeed, as stated by Farmer and Foley [32], the financial crisis highlighted all the weaknesses of DSGE models, based on too strict and unrealistic assumptions. Hence, by using these kinds of models, policy-makers can simulate artificial economies according to alternative scenarios to quantitatively explore the potential effects of each policy.

Most of the articles are published in collaboration. Indeed, single-authored documents are 254 out 1302, i.e., almost the 20% of the total production (see Table 1). In particular, we have that each article has 2 authors on average. Because of the complex nature of interactions that take place among authors over a period of time, the precise nature and magnitude of collaboration cannot be easily determined from standard metrics. To overcome this problem, bibliometric literature proposes the construction of the so-called collaboration index (e.g., see Ajiferuke et al. [33]), given by the ratio between the total number of authors of multi-authored documents and the total number of multiauthored documents. In the selected sample period, we observe a value of the index equal to 2.26, thus confirming the idea that on average there are two authors per document.

Looking at the sources publishing articles about agent-based modeling in finance, we find that Physica A is the most relevant journal with 90 articles published, followed by the Journal of Economic Dynamics & Control with 60 papers published on the topic. Among the 20 most productive sources, we found both journals specifically related to economics and finance, physical sciences, but also journals which audience are both physicists and economists such as PLOS One (with 22 published articles) and Quantitative Finance (with 39 documents). In terms of sources' impact, a citation analysis confirms that Physica A is the most influential source.

Given the above descriptive statistics, the aim of our paper can be summarized by testing the following two hypotheses:

(i) H1: The scientific production is characterized by two (or more) distinct clusters identifying specific research communities.

Table 1: Main statistics about the collection.

Main information	
Timespan	1992 : 2021
Sources (journals and books)	511
Documents	1302
Average years from publication	7.66
Average citations per documents	14.29
Average citations per year per doc	1.445
References	39299
Document distribution	
Article	1272
Review	30
Authors statistics	
Authors	2587
Author appearances	3498
Authors of single-authored documents	218
Authors of multiauthored documents	2369
Authors' collaboration	
Single-authored documents	254
Documents per author	0.503
Authors per document	1.99
Co-authors per documents	2.69
Collaboration index	2.26

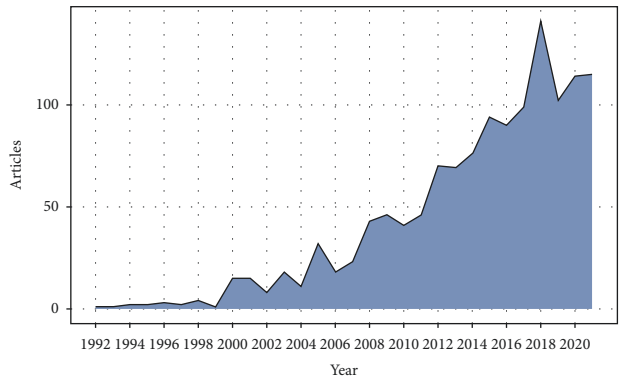

Figure 1: Annual production of articles about agent-based modeling.

(ii) H2: The two (or more) distinct research communities specialized in different topics.

The first hypothesis answers the following research question: is the scientific production of agent-based modeling in finance characterized by two or more distinct groups of research communities? If the hypothesis is accepted, it is natural to study the characteristics of such research communities in terms of the analyzed topics. Indeed, we have the second hypothesis to test, which answers the following question: in which topics are the different research communities specialized? This second question is relevant from a scientometric point of view because it can be that a very relevant topic for a given research community can be less critical for another one. For example, using the coupling technique in the context of financial bibliometric analysis, Khan et al. [8] documented the existence of four clusters specialized in different topics such as green finance, financial literacy, and big data. As another example, it is known that,

in the context of financial time series clustering, the econophysics community specializes in different topics compared to computer scientists and statisticians (e.g., see Mattera et al. [34]). There are many other examples of such distinctions. In this paper, we try to get deeper insights into the differences between the motor and declining topics in the different research communities through thematic maps.

4. Main Results

4.1. Identification of Research Communities with Coupling. In order to understand if two research communities really exist, we perform a bibliographic coupling analysis on journals (Kessler [9]). The idea behind bibliographic coupling analysis is that if two articles have similar bibliography probably the two works treat a related topic.

In a classical bibliographic coupling analysis, the unit of analysis is papers and their relatedness is determined based on the number of references they share. The number of references in common is normalized by considering the total number of papers cited by the two given documents. Obviously, the strength of the relationship of two documents is higher than more citations to other documents they share. The same logic can be extended to journals by aggregating the reference lists of their respective published papers, and the coupling strength of two journals (or more precisely, of the papers published on these journals) is defined as the size of the intersection of their cumulative reference lists.

Through coupling analysis, we identify 3 clusters of journals, the 33% of the total of sources in our collection. We do not couple sources that publish only one article on agent-based modeling. The distribution of the sources within clusters is shown in Table 2.

Table 2 clearly shows that the first cluster includes quantitative journals with a specific focus on mathematical and physical sciences. For example, it includes journals like Physica A, European Physical Journal B, Journal of Statistical Mechanics, Physical Review E, and others. These kinds of journals welcome contributions from physicists and econophysicists. The only (most relevant) interdisciplinary journals within this cluster are PLOS One and Quantitative Finance.

On the other side, the second cluster contains the majority of economics and financial journals. For example, cluster 2 includes the Journal of Economic Dynamic & Control, Computational Economics, Macroeconomic Dynamic, Economic Modelling, and much others.

Then, the third cluster includes journals of different types. Examples of sources are Expert Systems with Application and Information Sciences that have a specific focus on machine learning and statistics, and Sustainability and Energy Policy that are journals more related to energy and environmental sciences. Nevertheless, the third cluster also includes some economics-related journals, like Applied Economics and Review of Financial Studies, that published few contributions on agent-based modeling.

In general, the third group contains journals that published a lower amount of articles related to agent-based modeling. For example, the most productive journal on the topic is the JASSS with 22 articles, while in the first cluster there is Physica A with 90 papers and in the second one the Journal of Economic Dynamic & Control with 60 contributions. For this reason, we call the sources in the third cluster as residual group.

For each cluster of journals, we filtered the related papers obtaining 3 subcollections. Table 3 shows the main statistics of each subcollection.

Table 2: Most relevant journals within clusters.

Panel A: cluster 1—econophysics	
Sources	Articles
Physica A	90
Quantitative finance	39
PLOS One	22
Complexity	14
European Physical Journal B	13
Entropy	9
International Journal of Modern Physics C	9
Journal of Statistical Mechanics	9
IEEE Access	8
Physical Review E	8
Chaos	7
New Journal of Physics	7
Nonlinear Dynamics	7
International Journal of Theoretical and Applied Finance	6
Chaos, Solitions and Fractals	4
Panel B: cluster 2—financial economics	
Sources	Articles
Journal of Economic Dynamic and Control	60
Journal of Economic Interaction and Coordination	43
Computational Economics	33
Journal of Economic Behavior Organization	32
Economics	15
Advances in Complex Systems	13
Macroeconomic Dynamics	13
Economic Modelling	11
Journal of Evolutionary Economics	11
International Review of Financial Analysis	9
Discrete Dynamic in Nature and Society	8
Intelligent Systems in Accounting Finance Management	8
Economic Theory	7
Finance Research Letters	5
Panel C: cluster 3—residual	
Sources	Articles
JASS	22
Expert Systems with Applications	13
Sustainability	11
Energies	7
Evolutionary and Institutional Economics Review	7
Applied Economics	6
European Journal of Operational Research	6
International Journal of Information Technology Decision Making	5
Journal of Economic Theory	5
Review of Financial Studies	5
Energy Policy	4
Information Sciences	4
Journal of Monetary Economics	4
Mathematical Finance	4
Technological Forecasting and Social Change	4

Table 3: Main statistics about the subcollections.

Main information	Cluster 1	Cluster 2	Cluster 3
Timespan	2000 : 2021	1992 : 2021	1994 : 2021
Sources (journals and books)	47	62	64
Documents	341	402	217
Average years from publication	7.65	7.14	8.14
Average citations per documents	13.2	12.53	16.24
Average citations per year per doc	1.264	1.375	1.627
References	9430	11614	9213
Document distribution			
Article	330	397	214
Review	11	5	3
Authors' statistics			
Authors	687	687	574
Author appearances	956	996	617
Authors of single-authored documents	51	78	34
Authors of multiauthored documents	636	609	540
Authors' collaboration			
Single-authored documents	55	90	35
Documents per author	0.496	0.585	0.378
Authors per document	2.01	1.71	2.65
Co-authors per documents	2.8	2.48	2.84
Collaboration index	2.22	1.95	2.97

According to Table 3, the cluster with the longest timespan is the second one, i.e., the group containing the papers published by the financial economics community. It also contains the highest amount of documents, but lower documents over time ratio than the other two clusters.

Despite the lower timespan of the scientific production, the second cluster, i.e., the one including papers published by the econophysics community, is the one with the highest number of review articles on the topic.

In terms of authors' statistics, from Table 3 we note that clusters 1 and 2 have exactly the same number of authors. However, the financial economics cluster shows a higher amount of single-authored manuscripts. This evidence is also confirmed by the collaboration index that is equal to 1.95 versus the 2.22 of the econophysics cluster. The number of authors per document is also higher in the first cluster than the second.

The time series of the annual scientific production for each cluster is shown in Figure 2.

Interestingly, Figure 2 highlights that the econophysics community represented by the green line in the plot provided a higher production than the other two clusters between 2000 and 2007. Then, after the financial crisis the financial economics community rapidly increased the production of articles about agent-based modeling. This can be explained by the awareness about weaknesses of DSGE models, not able to properly model the complexity of financial markets with its agents.

Figure 2 confirms the evidence that the third cluster characterizes a less productive community. Indeed, the red line in the plot is always under the red and green ones. This is true especially after the financial crisis.

As recent evolution, we note a renewed interest in the econophysics community about agent-based modeling,

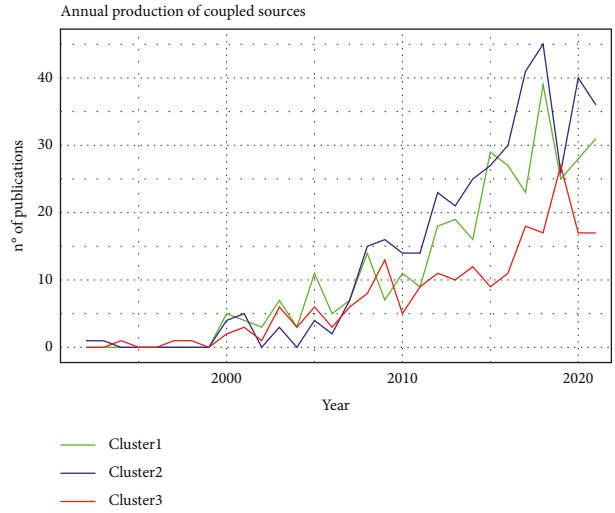

Figure 2: Annual production time series—all clusters.

since the green line has a positive inclination. Conversely, the blue line is showing a decreasing behavior, suggesting that the financial economics community is reducing its production about this topic in recent years.

The analyses conducted so far clearly suggest the presence of three groups of communities, identified on the basis of journals. In what follows, we provide a deeper investigation about the themes that characterize each group.

4.2. Identifying Cluster-Specific Emerging and Motor Topics with Thematic Maps. To compare the research fronts of the 3 communities, highlighting similarity ad differences, we perform a thematic analysis (Cobo et al. [35]) on each subcollection of papers. Thematic analysis is based on

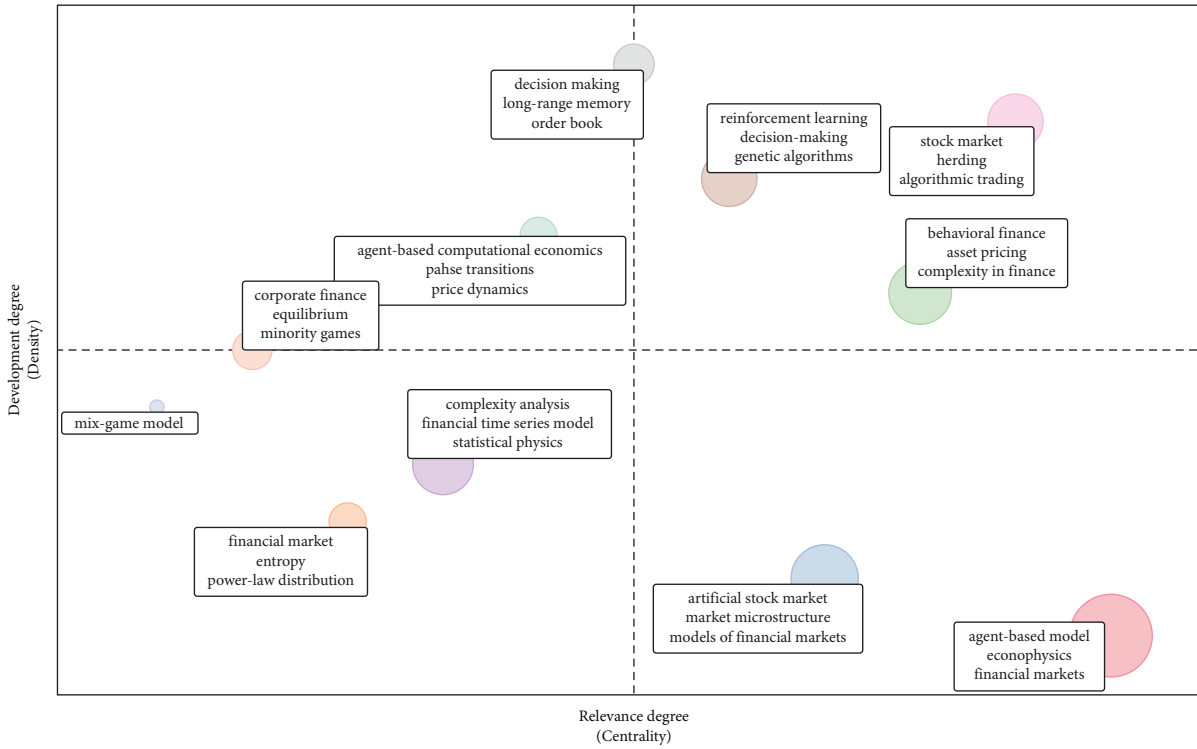

Figure 3: Thematic map—cluster 1.

network analysis tools. The starting point is to assume that each research field or topic can be represented as a set of strictly linked terms (e.g., keywords, terms extracted from titles and abstracts). In this paper, we consider author's keywords to represent the core of each publication. The relationship between couple of terms is measured by their co-occurrences (i.e., the number of times two terms appear together in a paper). We normalize the co-occurrences among terms with the association strength, as proposed by van Eck and Waltman [36]. The association strength is a normalized measure, where a 0 value means that the two terms never co-occur and a 1 value means that the terms co-occur in all papers. The association matrix among terms can be represented as an undirected weighted graph. By performing a community detection procedure on this graph, it is possible to identify subset of strictly related terms, reflecting the different topics embodied in the collection. The themes identified by the community detection are summarized on a thematic diagram (Callon et al. [37]), according to *Callon centrality* (x-axis) and *Callon density* (y-axis). Centrality can be interpreted as the relevance of the topic in the entire research domain, while density reflects its development. Having in mind this, it is possible to define four typologies of topics:

(i) Topics in the upper-right quadrant are the motor themes. They are characterized by both high centrality and density. This means that they are well developed and relevant for the domain.

(ii) Topics in the lower-right-hand quadrant are basic and transversal topics. They are characterized by high centrality and low density. These themes are relevant for a research field and pertain to general topics transversal to its different research areas.

(iii) Topics in the lower-left quadrant are both weakly developed and marginal. They have low density and low centrality, mainly representing either emerging or disappearing topics.

(iv) Topics in the upper-left-hand quadrant are the highly developed and isolated, named as niche themes. They have well-developed internal links (high density) but unimportant external links and thus are of only limited relevance for the field (low centrality).

Each topic is labeled with the its most occurring keywords, assuming that it is representative of the topic itself. The size of topic is proportional with the total occurrences of the keywords that it includes.

As previously highlighted, the first cluster contains the journals devoted to econophysicists. Figure 3 shows the thematic map for the econophysics cluster.

The keyword econophysics occurs very frequently for articles included in this group, suggesting that the assigned label is correct. Emerging cluster's topics are the simulation of artificial stock markets for the analysis of market microstructure, microstructure noise, and the behavior of traders. Then, motor topics can be identified in behavioral finance-related, e.g., herding, with application to asset pricing and trading. In other words, it seems that the interest of econophysics community is mainly devoted to more individual-oriented aspects of finance. As briefly discussed

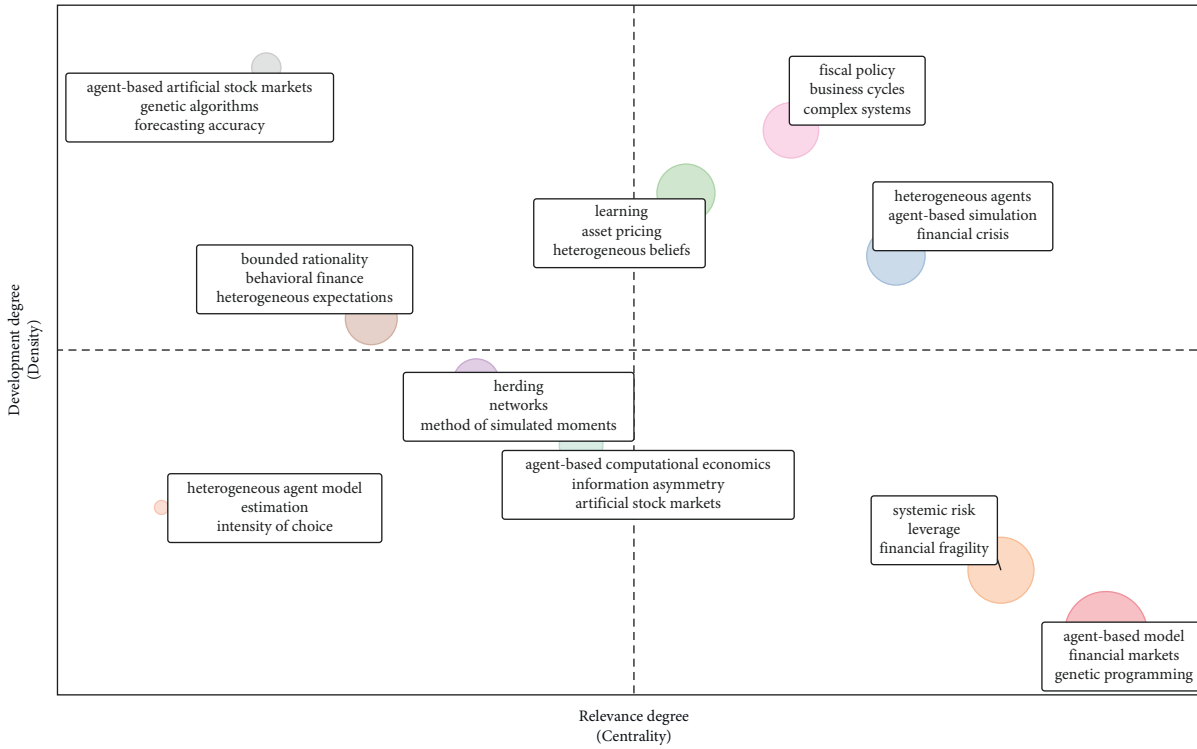

Figure 4: Thematic map—cluster 2.

in Section 2, a relevant topic for econophysics is still represented by behavioral finance. Behavioral finance aims at improving financial modeling based on the psychology of the investors. In the context of agent-based modeling, it seems that the econophysics community is more specialized in building models in which agents make investment decisions according to utility functions reflecting their psychology. Although this topic is a tradition in econophysics, it still represents a motor topic deserving increasing research efforts.

Niche topics are represented by corporate finance application of the agent-based modeling. Conversely, long-range dependence seems to be a niche topic that is becoming very popular. In particular, the interaction between decision making under long-range dependence and market microstructure noise is of interest. Indeed, such topics are in the middle between the plot quadrant identifying niche and motor topics. However, the analysis of power-law distributions and entropy seems to be a declining topic that has gotten more attention in the past years. Another declining topic is the statistical modeling of financial time series, which has become more important for econometricians and statisticians than for academics in econophysics.

The second cluster includes the journals devoted to financial economics community. Figure 4 shows the thematic map for this cluster.

In the financial economics community, the analysis of themes related to economics, such as fiscal policy and business cycle analysis, represents motor ones. Similarly, also the use of agent-based modeling to study the effect of financial crisis and the interaction between finance and macroeconomic shocks are motor topics. Then, the analysis of systemic risks and financial fragility of markets are basic and central topics not very dense but relevant for this cluster. The use of agent-based models employing learning and asset pricing seems to be an important emerging topic for this group. The learning approach plays a central role in modern macroeconomics, and this is confirmed by Figure 4. In models with learning, the economic agents form their expectations by estimating and updating forecasting models in real time (see, e.g., [38]). Therefore, we find that the use of learning in asset pricing problems is expanding topic and deserves future research efforts.

Studies devoted on bounded rationality and, more in general, behavioral finance based on heterogeneous expectations can be identified as niche topics as well for this cluster. Similarly, herding behavior and network structures in financial markets seem to be marginal topics. This is a significant difference with respect to the econophysics cluster (Figure 3), for which behavioral finance is a very important topic. This evidence highlights a clear difference between the two communities: while econophysics is more oriented on studying the complexity arising because of, among the others, investors' psychology and beliefs, the economics community is more focused on the interaction between macroeconomics and finance, thus adopting a more aggregate perspective in the analysis of the problems.

The third cluster identifies a mixing community characterized by a lower production about agent-based modeling. Figure 5 shows the related thematic map.

This cluster includes papers which cannot be clustered with any of the two main research communities, thus

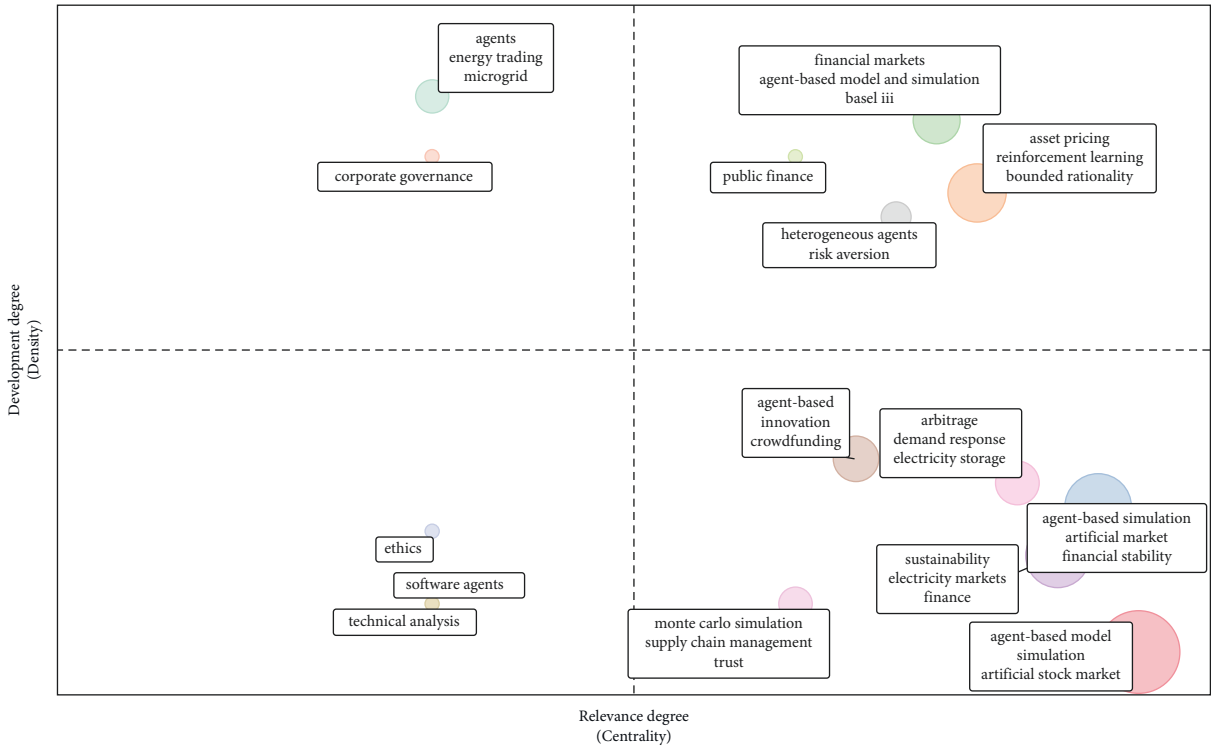

Figure 5: Thematic map—cluster 3.

forming a sort of residual cluster. In fact, from the thematic map in Figure 5, we observe that the basic topics of articles included in this group are of a great variety. Examples are given by sustainability, innovation, and crowdfunding, supply chain as well as more commodities-related topics such as the electricity storage. Overall, it seems that central topic of this third cluster is managerial-related.

On the side of motor topics, Figure 5 identifies the application of reinforcement learning for asset pricing, which is a more individual-specific topic, but also to the analysis of financial stability regulation, such as Basel III, and public finance which are topics studying more problems following an aggregate perspective. The analysis of energy trading and corporate governance are niche topics.

5. Discussion and Final Remarks

As specified in the introduction, agent-based modeling involves using computational models to reproduce interactions between economic agents in complex systems. Agent-based models are considered a competitor of the standard dynamic stochastic general equilibrium (DSGE), based on much more strict assumptions.

The bibliometric analysis conducted so far highlights exciting points of discussion. First, we have seen that the agent-based models became very popular after the 2008 financial crisis. This is evident by looking at the total amount of papers published after 2008.

From the first analysis of relevant sources, we found an interesting distinction between journals devoted to economics and finance and those related to physical sciences. Based on this preliminary evidence, we conducted a coupling analysis on journals to assess if two separate communities publishing about agent-based models in finance exist.

Indeed, it is clear that while financial economists tend to publish in economics-related journals, physicists use to publish in physics journals. By performing the coupling algorithm based on the similarity in papers' references, we found the existence of three separate groups.

Most papers published in physical sciences journals are included in the first group. Therefore, we labeled it as *econophysics* cluster. Then, in the second cluster, most sources are published in financial economics journals. In the third group, instead, we found the presence of journals that do not use to publish articles on agent-based models, i.e., that are less productive. Hence, we labeled this third cluster as *residual*.

The thematic analysis has been conducted with respect to the different clusters. The findings highlight interesting points of discussion.

First, all the clusters contain a general agent-based model topic, identified as a fundamental topic. However, it is important to note that the keyword econophysics is present only for the papers placed in the first cluster, i.e., confirming the presence of a cluster characterized by the econophysics community.

The three clusters differentiate each other in terms of treated topics. In particular, we observe that many topics are present within more than one cluster but with a different degree of relevance. For example, let us consider the case of herding behavior modeling. In the econophysics cluster, it is

a motor topic, while for the financial economists' community, it is an emerging topic. In this sense, econophysicist anticipated the financial economists. However, even if this topic is quite traditional in econophysics, it still represents a motor topic deserving increasing research efforts.

Another interesting example is the case learning. In both the communities, it is an important topic. However, in the two communities it takes different forms. In the case of econophysics, learning is intended from the deep learning point of view. Indeed, in the reinforcement learning there is an agent which interacts with an environment through a reward function. In reinforcement learning algorithms the agents take actions with the aim of maximizing such a reward. Differently, in macroeconomic learning the agents form their expectations by updating forecasts in real time. The kind of complexity associated with the two approaches is quite different.

Then, there is a net distinction in the applicative domain of agent-based models between the two communities. Indeed, the econophysics community is more specialized in building models in which agents make investment decisions according to utility functions reflecting their psychology. Although this topic is a tradition in econophysics, it still represents a motor topic deserving increasing research efforts. In other words, while the econophysics community is only interested in treating the case of the stock market, the financial economics literature commonly models the interaction between financial markets and macroeconomic policies. Indeed, papers dealing with keywords like business cycle and fiscal policy that identify a macroeconomic theme are a motor for the second cluster and are absent for papers placed within the first cluster.

Moreover, from thematic maps, we also understand that an important topic treated by the financial economics community is related to financial stability and systemic risk. We did not find these topics in the papers belonging to the econophysics cluster. Vice versa, in the first cluster, we observed a higher relevance to behavioral finance topics. This fact highlights another clear difference between the two communities: while econophysics is more oriented on studying the complexity arising because of, among the others, investors' psychology and beliefs, the economics community is more focused on the interaction between macroeconomics and finance, thus adopting a more aggregate perspective in the analysis of the problems. Studies devoted on bounded rationality and, more in general, behavioral finance are less relevant in the economics cluster than in the econophysics one.

In summary, our bibliometric analysis highlighted the presence of well-separated community groups identified by journals in which the papers are published. This aspect represents a contribution to our paper. Indeed, the difference between this paper and previous studies mainly lies in the distinction between qualitative and quantitative approaches used in the review. Because of the intrinsic difference in the approaches, identifying these clusters with their own motor and emerging topics has never been highlighted.

These findings open up to add comments. First of all, the two communities are specialized in different topics, i.e., behavioral finance and individual-oriented (econophysics) versus macroeconomics and aggregate-oriented (economics). Second, from the above analysis, it seems that the two communities do not collaborate and read each other. This can be problematic in terms of future developments of agent-based modeling, because the two research communities have their expertise, and the research would surely benefit from their intersection.

We think that this contribution can push researchers from both communities to interact more in the near future. Furthermore, due to the differences in the trending topic between the two communities, we also think that findings can guide researchers in identifying the most suitable journal for their last research on the topic.

Data Availability

Data source is Web of Science (WoS). Results of analysis is available under request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] R. Cont, "Empirical properties of asset returns: stylized facts and statistical issues," *Quantitative Finance*, vol. 1, no. 2, p. 223, 2001.

[2] A. Chakraborti, I. M. Toke, M. Patriarca, and F. Abergel, "Econophysics review: II. Agent-based models," *Quantitative Finance*, vol. 11, no. 7, pp. 1013–1041, 2011.

[3] S. H. Chen, C. L. Chang, and Y. R. Du, "Agent-based economic models and econometrics," *The Knowledge Engineering Review*, vol. 27, no. 2, pp. 187–219, 2012.

[4] J. P. Huang, "Experimental econophysics: complexity, self-organization, and emergent properties," *Physics Reports*, vol. 564, pp. 1–55, 2015.

[5] M. Aria and C. Cuccurullo, "bibliometrix: an R-tool for comprehensive science mapping analysis," *Journal of informetrics*, vol. 11, no. 4, pp. 959–975, 2017.

[6] M. Aria, M. Misuraca, and M. Spano, "Mapping the evolution of social research and data science on 30 years of Social Indicators Research," *Social Indicators Research*, vol. 149, no. 3, pp. 803–831, 2020.

[7] A. Paltrinieri, M. K. Hassan, S. Bahoo, and A. Khan, *A Bibliometric Review of Sukuk Literature*, International Review of Economics & Finance, 2019.

[8] A. Khan, J. W. Goodell, M. K. Hassan, and A. Paltrinieri, "A bibliometric review of finance bibliometric papers," *Finance Research Letters*, vol. 47, Article ID 102520, 2022.

[9] M. M. Kessler, "Bibliographic coupling between scientific papers," *American Documentation*, vol. 14, no. 1, pp. 10–25, 1963.

[10] G. Fagiolo and A. Roventini, "Macroeconomic policy in DSGE and agent-based models redux: new developments and

challenges ahead," *The Journal of Artificial Societies and Social Simulation*, vol. 20, no. 1, 2017.

[11] G. Fagiolo, M. Guerini, F. Lamperti, A. Moneta, and A. Roventini, "Validation of agent-based models in economics and finance," in *Computer Simulation Validation. Simulation Foundations, Methods and Applications*, C. Beisbart and N. Saam, Eds., Springer, Cham, 2019.

[12] G. J. Stigler, "Public regulation of the securities markets," *Journal of Business*, vol. 37, no. 2, p. 117, 1964.

[13] F. Slanina, "Critical comparison of several order-book models for stock-market fluctuations," *European Physical Journal B: Condensed Matter Physics*, vol. 61, no. 2, p. 225, 2008.

[14] M. B. Garman, "Market microstructure," *Journal of Financial Economics*, vol. 3, no. 3, p. 257, 1976.

[15] D. K. Gode and S. Sunder, "Allocative efficiency of markets with zero-intelligence traders: market as a partial substitute for individual rationality," *Journal of Political Economy*, vol. 101, no. 1, p. 119, 1993.

[16] R. Cont and J. P. Bouchaud, "Herd behavior and aggregate fluctuations in financial markets," *Macroeconomic Dynamics*, vol. 4, no. 2, p. 170, 2000.

[17] M. Raberto, S. Cincotti, S. M. Focardi, and M. Marchesi, "Agent-based simulation of a financial market," *Physica A: Statistical Mechanics and Its Applications*, vol. 299, no. 1-2, p. 319, 2001.

[18] T. Lux and M. Marchesi, "Volatility clustering in financial markets: a microsimulation of interacting agents," *International Journal of Theoretical and Applied Finance*, vol. 3, no. 4, pp. 675–702, 2000.

[19] C. Chiarella and G. Iori, "A simulation analysis of the microstructure of double auction markets," *Quantitative Finance*, vol. 2, no. 5, p. 346, 2002.

[20] J. P. Bouchaud, M. Mezard, and M. Potters, "Statistical properties of stock order books: empirical results and models," *Quantitative Finance*, vol. 2, no. 4, pp. 251–256, 2002.

[21] M. Potters and J. P. Bouchaud, "More statistical properties of order books and price impact," *Physica A: Statistical Mechanics and Its Applications*, vol. 324, no. 1-2, p. 133, 2003.

[22] D. Challet and R. Stinchcombe, "Analyzing and modeling 1+1d markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 300, no. 1-2, pp. 285–299, 2001.

[23] P. Bak, M. Paczuski, and M. Shubik, "Price variations in a stock market with many agents," *Physica A: Statistical Mechanics and Its Applications*, vol. 246, no. 3-4, pp. 430–453, 1997.

[24] S. Maslov, "Simple model of a limit order-driven market," *Physica A: Statistical Mechanics and Its Applications*, vol. 278, no. 3-4, pp. 571–578, 2000.

[25] S. Mike and J. D. Farmer, "An empirical behavioral model of liquidity and volatility," *Journal of Economic Dynamics and Control*, vol. 32, no. 1, pp. 200–234, 2008.

[26] G. F. Gu and W. X. Zhou, "Emergence of long memory in stock volatility from a modified Mike–Farmer model," *Europhysics Letters*, vol. 86, no. 4, pp. 48002–48006, 2009.

[27] A. Kirman, "On mistake beliefs and resultant equilibria," in *Individual Forecasting and Aggregate Outcomes: Rational Expectations Examined*, R. Frydman and E. Phelps, Eds., pp. 147–165, Cambridge University Press, Cambridge, 1983.

[28] A. P. Kirman, "Whom or what does the representative individual represent?" *The Journal of Economic Perspectives*, vol. 6, no. 2, p. 117, 1992.

[29] A. Kirman, "Ants, rationality, and recruitment," *Quarterly Journal of Economics*, vol. 108, no. 1, pp. 137–156, 1993.

[30] A. Kirman, "Reflections on interaction and markets," *Quantitative Finance*, vol. 2, no. 5, p. 322, 2002.

[31] A. Liberati, D. G. Altman, J. Tetzlaff et al., "The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration," *Journal of Clinical Epidemiology*, vol. 62, no. 10, pp. e1–e34, 2009.

[32] J. D. Farmer and D. Foley, "The economy needs agent-based modelling," *Nature*, vol. 460, no. 7256, pp. 685-686, 2009.

[33] I. Ajiferuke, Q. Burell, and J. Tague, "Collaborative coefficient: a single measure of the degree of collaboration in research," *Scientometrics*, vol. 14, no. 5-6, pp. 421–433, 1988.

[34] R. Mattera, M. Misuraca, G. Scepi, and M. Spano, "Clustering of financial time series: a bibliometric analysis," in *Proceedings of the 16th International Conference on Statistical Analysis of Textual Data*, vol. 2, pp. 584–590, VADISTAT Press/Edizioni Erranti, 2022.

[35] M. J. Cobo, A. G. López-Herrera, E. Herrera-Viedma, and F. Herrera, "An approach for detecting, quantifying, and visualizing the 247 evolution of a research field: a practical application to the fuzzy sets theory field," *J. Infometr*, vol. 5, pp. 146–166, 2011.

[36] N. J. v. Eck and L. Waltman, "How to normalize cooccurrence data? an analysis of some well-known similarity measures," *Journal of the American Society for Information Science and Technology*, vol. 60, no. 8, pp. 1635–1651, 2009.

[37] M. Callon, J. P. Courtial, and F. Laville, "Co-word analysis as a tool for describing the network of interactions between basic and technological research: the case of polymer chemsitry," *Scientometrics*, vol. 22, no. 1, pp. 155–205, 1991.

[38] G. W. Evans and S. Honkapohja, "Learning and macroeconomics," *Annual Review of Economics*, vol. 1, no. 1, pp. 421–449, 2009.

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Review Article

Longitudinal Study of Credit Union Research: From Credit-Provision to Cooperative Principles, the Urban Economy and Gender Issues

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Credit unions are one of the most widely established corporate entities in the financial systems of most of the world's nations. Their historical support to the financing needs of small savers, as well as their assimilation into the framework of contemporary microfinance, gives them an important specific weight in the economic-financial literature of our time. In this sense, our research has carried out a systematic review of the main contributions (articles in scientific journals) focused on the area of credit unions over the period 1936–2020, using Scopus and WoS as bibliographic databases. In summary, the main countries, journals, authors, articles, and the main collaborative research networks at the level of authors or countries have been analyzed. In the same way, the implementation of strategic diagrams based on Callon's procedure has facilitated the classification of the most important terms linked to financial cooperativism, which has served to detect future lines of research related to the terms (among others): asymmetric-information, capital-provision, cooperative-principles, customer-reduction, gender-issues, neoinstitutionalism, poverty, and urban-economy.

1. Introduction

It was not always possible for all social classes to access credit. Until well into the nineteenth century, only the large industrial conglomerates of that time could obtain financing, excluding the most disadvantaged strata of society, which inhibited the growth of small manufacturing businesses or peasants with scarce financial resources. Access to credit for less well-off individuals was the work of several English philanthropists, the so-called "Rochdale Pioneers," who founded in 1844 "The Rochdale Society of Equitable Pioneers," a consumer cooperative that would eventually lay the foundations of the modern cooperative movement and, obviously, of today's credit unions [1]. Among the leading figures of the cooperative movement, names such as F. W. Raiffeisen (1818–1888), H. Schulze-Delitzsch (1808–1883), A. Desjardins (1854–1920), and E. Filene (1860–1937) stand out, who were the creators of the first credit unions in Germany, Canada, and the United States, respectively [2]. It should be borne in mind that the first credits granted by these institutions in their beginnings were valued at several cents on the dollar. In contrast, at present, they represent the second source of global financing after conventional banking [3], serving the interests of citizens with fewer economic resources [4]. At the same time, they have been revealed as a necessary instrument to combat material poverty [5], especially in rural or agrarian areas [5–7].

The humanist spirit of the Rochdale pilgrims is still present in the daily work of these financial institutions since the guidelines set by those social benefactors are still followed according to the "Rochdale Principles" [2]. That is, a set of postulates that reflect the character and circumstances

of the founders of the cooperative movement, faithfully transferred today to the organizational structure and *ad hoc* legislation of these corporate entities [8]. The founders came from different countries and professed diverse religions and ideologies. Hence, the internationalist vocation of these organizations, their political-religious neutrality, and a consideration of social benefit are utterly different from that of mere economic return [9], whereby the "non-profit" concept [10] prevails over any other type of consideration. For these reasons, financial institutions linked to cooperativism went from being residual associations of just a handful of members to substantially increasing their business volume [11], being able to generate synergies among their members, as well as economies of scale from the capital provided by small savers [12]. These elements have led to a growing demand for the services offered by credit unions [13–15], consolidating a series of practices that, by definition, entail considerably less risk than those of conventional banking [16].

The altruistic-cooperative scheme that defines Credit Unionism has adapted to the passing of time since the principle of neutrality has facilitated its expansion throughout the planet, giving rise to innovative initiatives such as the "Fountain of Love Credit Union" in Indonesia [17]. This same principle embodies the fact that the solidarity vocation of these institutions allowed them to be commonly accepted by various religious denominations. Credit unions found broad support from specific sectors of the Catholic Church from the perspective of Catholic social teaching [18]. Likewise, it has been perfectly assimilated by contemporary Islamic Banking and Finance by creating inclusive financial institutions in line with the principles of this religion [7, 19]. They represent a fundamental tool for supporting and disseminating microcredits [5, 17, 20]. Consequently, according to the supranational institution in charge of the regulation of these institutions, the World Council of Credit Unions [21], their importance in the world economic-financial panorama can be summarized in the following figures: there are more than 86,000 institutions present in all continents that group together more than 300 million members from 118 different countries.

Therefore, due to the historical significance of these corporate entities in the financial systems of most countries, to their proactive welfare work against social exclusion, to their strong presence in the rural environment of both developed and underdeveloped countries, or the booming volume of credit they finance worldwide, these institutions are worthy of exhaustive bibliometric analysis, with a sufficiently long time horizon to detail the main aspects and defining features that have surrounded their study, this being the primary objective of this research.

Currently, bibliometric methods and models have allowed metadata to go from being simple microfiles of structured information to become an inexhaustible source of descriptive or visual resources [22], capable of clarifying any discipline or domain of knowledge. This phenomenon is due to the fact that scholars have an increasing number of bibliometric tools and applications [23] (some of them freely available to the scientific community [24]), which have led to the emergence of bibliometric software over the last 25 years. Among this wide range of applications are BibExcel [25], Bibliometrix [26], CiteSpace [27], HistCite [28, 29], NetDraw [30], Network Workbench [31], Pajek [32], Sitkis [33], UCINET [34], or Leydesdorff Toolkit [35].

However, in this research, two bibliometric applications, whose versatility has led them to become a standard in the applied bibliometric analysis, have been used complementarily: VOSViewer [36] and SciMAT [37]. The former is a significant improvement over multidimensional scaling techniques, being particularly suitable for visualization, clustering, and mapping of bibliometric networks [38–41]. By its part, SciMAT [42–44] bases its analytical potential on the use of co-word analysis for the construction of strategic diagrams representative of any discipline or knowledge domain [45].

Both tools have been applied at the same time on two reference indexes in the scientific literature: Scopus (Elsevier) and Web of Science (Clarivate Analytics) (hereinafter Scopus and WoS, respectively). Such implementation allows mitigating the relative problems of working with both indexes simultaneously until there is a plausible integration of these bibliographic platforms [28]. Likewise, the use of quantitative techniques or the visualization of bibliometric networks has made it possible to describe the evolution of the study of credit unions over a long period of analysis (1936–2020) reliably, detailing its defining facts and, above all, its multidisciplinary nature, given that its study is linked to other branches of knowledge such as economics, politics, history, and philosophy.

The remaining part of this manuscript is structured as follows: section 2 contains a bibliographical review of the financial cooperative phenomenon. Next, section 3 details the methodology followed by this research, while section 4 presents the results obtained. Finally, section 5 specifies the conclusions to be drawn from this research work, including a series of future lines of research.

2. Literature Review

Such has been the impact of credit unions on the economic panorama of the last century that they have become part of recent economic history. In this sense, Guinnane [46, 47] analyzes their impact on the economic structure of the Reich until 1914 or documents how implementing the original German model (Raiffeisen's model) in Ireland initially caused more problems than benefits, given that the idiosyncrasies and socio-cultural differences between the two peoples were enormous [48]. Other research such as Thomas et al. [49, 50] link the birth of cooperativism to the expansion of the socialist movements of the nineteenth century, while Hibberd [51] denies the weight that tradition always gave to the Rochdale Pioneers, considering that this institution was historically mythologized. There is no doubt that the U.K. was the driving force behind the cooperativism and has often been the source of seminal research. Focusing on this nation, Ward et al. [52] underline the prolonged growth of these institutions at the national or regional level. Likewise, Ward et al. [53] analyze the link between the characteristics and

location of credit unions and their financial success, which, on the other hand, is also strongly associated with environmental variables [54].

The global expansion of credit unions is evidenced by the countless number of studies spread over the five continents, both in developed and developing countries [55, 56]. Thus, we find works on initiatives carried out by credit unions in Albania [57], Australia [58], Bulgaria [59], Cameroon [60], Ethiopia [61], Finland [62], Indonesia [17], Ireland [63], Japan [64], United States [65], etc. Research has gradually diversified into works analyzing the conceptual framework of its operation from theoretical [66–68] and empirical perspectives [63, 69, 70].

In the first case, Smith [71] develops a theoretical framework in which the decision-making processes of credit unions are modelled. They always have to be implemented under strict ethical-moral conditions, given the solidarity nature of these institutions [72], which makes them regulated by specific legislation [58, 63, 73], completely different from conventional banking. From the empirical point of view, there are multiple works focused on the rural environment [5, 7, 61, 74], on the credit needs of agrarian communities [57, 59, 75], and microfinance [5, 7, 15, 17, 57, 59, 60], as one of the few viable alternatives to eradicate poverty in the poorest nations [76, 77] and the most disadvantaged local communities of developed countries [78, 79]. In this sense, Yunus [80] undoubtedly played an essential role in conceptualizing financial credit as an inalienable right of all human beings [81].

Because of the importance of financial cooperativism as a mechanism for social cohesion, Khafagy [82] highlights the importance of political institutions as a factor in the development of credit unions, which must be taken into account when making economic policy measures [83], or any other integrating measure that facilitates equitable distribution among their members [84]. In this way, considerable benefits are generated for the entire social collective such as public health [85], one of the many initiatives carried out by these social entities.

Independently of their beneficial vocation, they also pursue obtaining an economic benefit to sustain their ordinary operations. For this reason, there is a predominance of research aimed at evaluating their financial performance [59, 62, 63, 86–90], their growth patterns [52, 70, 73, 91, 92], life cycle [93, 94], degree of efficiency in credit allocation [54, 59, 61, 64], or their capacity to develop economies of scale [12, 95–98] according to its relative size [11, 12, 70, 99], which, as a general rule, is usually lower than that of commercial banking institutions.

Another defining characteristic of today's credit unions is the greater degree of diversification of their operations [87, 100] and their capacity to establish cooperative integration networks [88]. These networks have given them greater proximity to end customers, reducing the cost of credit available to the public [101], and they are an alternative to the mergers, which have also occurred among this type of institution [75, 90].

Other studies specifically address different aspects of the contemporary reality of this sector, such as the implementation of new technologies that have revolutionized the business channels of credit unions concerning their traditional operations [102] or the links between the objectives pursued by these entities and the establishment of the U.N. Development Goals [85, 103, 104]. Concerning the methodology applied in the analysis of financial cooperativism, it could be said that its multidisciplinary nature has been matched by multiple methodological perspectives, among which the following approaches could be mentioned: statistical and econometric models [13, 14, 58, 70, 85], stochastic frontier analysis [54], neural networks [105, 106], Gibrat's rule of proportionate effect [52], data development analysis [89], and genetic algorithms. [105].

3. Methodology

This research has carried out an exhaustive analysis of the bibliographic production related to credit unions from 1936 to 2020. Figure 1 shows the flow diagram of the document search [107].

In line with other bibliographic works [108–110], a systematic research design has been followed, subdivided into 4 phases: determination of terms on which the bibliometric analysis is performed (I); selection of databases, search, cleaning, and tabulation of records (II); use of bibliometric tools to obtain information maps and tables representative of the analyzed phenomenon (III); and analysis of the outputs obtained (IV). Figure 2 summarizes the methodological design implemented.

The terms that best fit a comprehensive review of any aspect related to the phenomenon of financial cooperativism were specified during the first phase. The three key concepts on which the bibliometric analysis was based were selected: credit union, credit cooperative, and financial cooperative. In the second phase, it was estimated which databases would be used to obtain the bibliographic base, choosing Scopus and WoS since they have a proven reputation in the scientific field from among the number of databases currently available to the scientific community [111]. The decision to implement both of them was justified by the fact that Scopus represents the most comprehensive bibliographic database in terms of indexed items, while WoS is the one that introduces a wider range of interdisciplinary contents [110, 112–114]. Subsequently, an exhaustive search was carried out in the Title field for the key terms determined in the first phase using Boolean operators ("credit union" OR "credit cooperative" OR "financial cooperative"). In order to homogenize the results obtained, this search was subject to two restrictions: scientific production expressly written in English (1) in the form of articles (2), discarding any other type of publication (e.g., books, chapters, conferences, editorials, and notes).

As a horizon for the research, the period 1936–2020 was selected, a time frame long enough to reliably analyze the depth, multidisciplinarity, and relevance of financial cooperativism. The search was carried out in October 2021, and since this study collects the bibliographic production of each year in its entirety, no bibliographic record corresponding to 2021 was included. For illustrative purposes, the

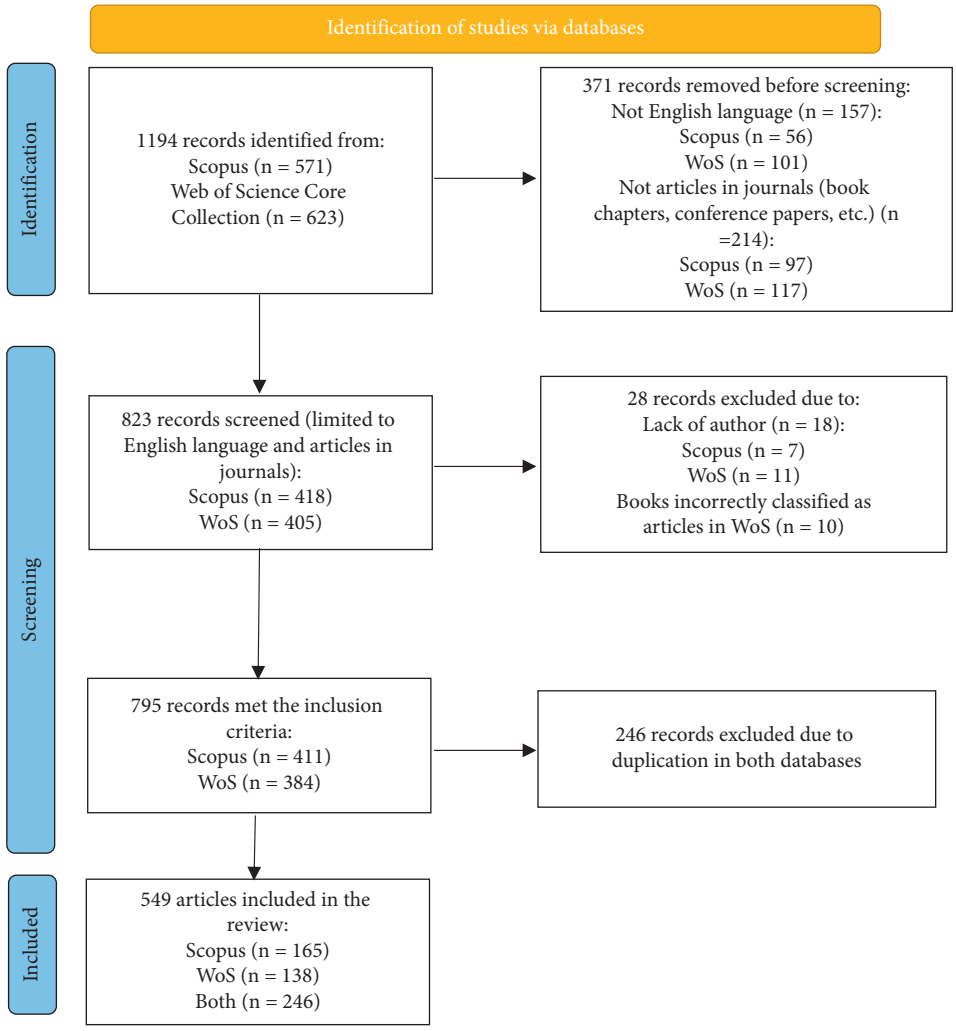

Figure 1: PRISMA flow diagram for systematic review.

lower interval of the established period (1936) is represented by "Rural cooperative credit unions" [6], while among the items forming the upper interval (2020), we can find "Drivers of credit union penetration: An international analysis" [115]. Note that this bibliometric study covers practically half of the years that have elapsed since the movement's founding in 1844 to the present day. Next, the bibliographic databases' metadata was cleaned using the JabRef 5.4 program. Basically, this task consisted of eliminating duplicate records in the same index, correcting records lacking an author or affiliation, or correcting names and surnames of authors that remained incomplete. From this point on, the bibliographic database was conveniently tabulated using MS Excel 2019, which made it possible to obtain the final arrangement of bibliographic records shown in Figure 3.

According to Figure 3, the records used in this research corresponding to the databases implemented in the bibliographic analysis can be clearly observed. More specifically, 549 bibliographic items were incorporated: 165 exclusives to Scopus, 138 exclusives to WoS, and 246 commons to both indexes. To obtain a greater precision about the dimension of the bibliographic analysis, Table 1 represents the core of the research, highlighting the main characteristics of the bibliographic production studied. In this sense, the study period was subdivided into two representative subperiods: 1936–2004 and 2005–2020. It is significant to observe an unusual growth in the bibliographical production related to financial cooperativism during the last fifteen years. Indeed, the number of articles, journals, authors, countries, and organizations has increased significantly from 2005 onwards compared to the 1936–2004 subperiod. On the other hand, the indicators relating to citations are higher during the first subperiod. This fact may be fundamentally due to the enormous impact of the classic and pioneering works in the pre-existing literature focused on the study of credit unions [66, 86, 91, 101, 106].

In the third phase of the research, two bibliometric applications were implemented in a complementary manner: VOSViewer v1.16.17 and SciMAT v1.1.04. The first application allowed the mapping and visualization of cooperative bibliometric networks [116] at the level of key topics, the leading authors in the field of financial cooperativism, and the countries from which the most relevant

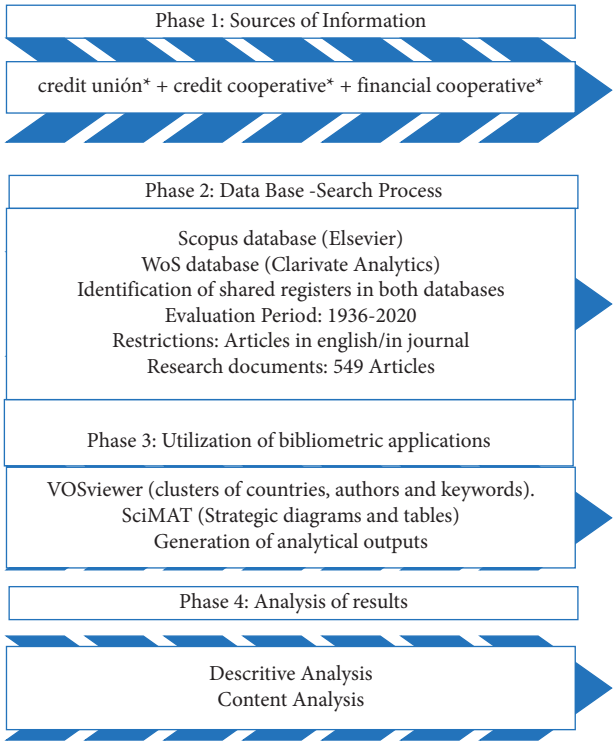

Figure 2: Methodological flowchart.

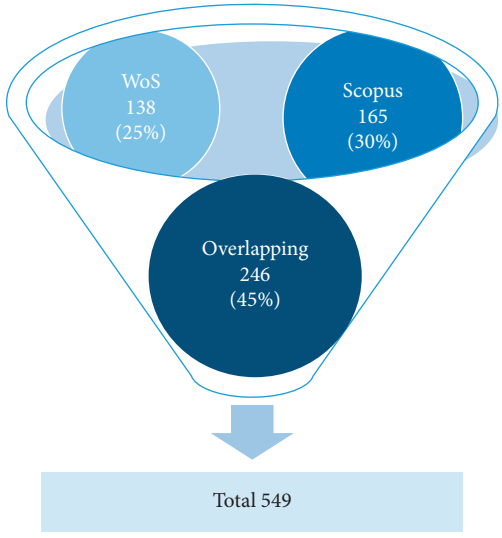

Figure 3: Number of articles in Scopus and Web of Science database (1936–2020).

research originates. The use of SciMAT resulted in the creation of strategic diagrams obtained from the systematic clustering of the most important research terms, thus making it possible to observe the enumeration of a series of future lines of research arising from this study.

Additionally, the tabulation of the data utilizing Excel has served as support for the elaboration of descriptive figures and analytical tables in which key indicators in the area of bibliometrics have been used, such as the h-index (Hirsch index) [117–119] and SJR (SCImago Journal Rank)

Table 1: Summary of data.

Data	1936–2004	2005–2020	Total
Number of articles	240	309	549
Number of journals	133	210	321
Number of authors	293	562	829
Number of countries	17	51	55
Number of organizations	197	446	639
Number of citations	3,971	1,830	5,801
Average citations/article	17	6	11
Average citations/authors	14	3	7

Source: own elaboration.

[120], a key bibliometric indicator that uses the Google PageRank algorithm in its analysis. Finally, the fourth phase involved a double analysis of the results obtained (descriptive and content analysis), which is detailed in the following section.

4. Results

Figure 4 shows an overview of the evolution of credit union research using Scopus and WoS together over the period 1936–2020. A first distinctive feature is that the number of citations is practically residual between 1936 and 1970. During the 1970s, the number of citations experienced moderate growth, motivated by the appearance in 1977 of the classic manuscript "Recent Research on Credit Unions: A Survey" [121]. The growth of citations began to be practically exponential from 1994 onwards, given that during this same year, three papers were published that would eventually have an enormous impact on the literature in terms of citations: "A time to grow and a time to die: Growth and mortality of credit unions in New York City, 1914–1990," "Thy neighbor's keeper: The design of a credit cooperative with theory and a test," and "A Failed Institutional Transplant: Raiffeisen's Credit Cooperatives in Ireland, 1894–1914" [48, 66, 91].

Subsequently, three significant "peaks" can also be observed: in 1996, 1998, and 2001, resulting from the impact of several seminal articles such as "A comparison of neural networks and linear scoring models in the credit union environment," "Availability and cost of credit for small businesses: Customer relationships and credit cooperatives," and "Cooperatives as information machines: German rural credit cooperatives, 1883–1914" [47, 101, 106]. Regarding the dating of the records included in the databases used, the oldest in Scopus is from 1945 ("How the Credit Union Serves Teachers" [122]), while the oldest in WoS is from 1956 ("The Federal Credit Union System: A Legislative History" [123].

Within the category of articles contained in both indexes ("overlapping articles") can be found the oldest item, dating from 1936 ("Rural cooperative credit unions" [6]). Likewise, four stages can be distinguished in the evolution of the records exclusively contained in Scopus and WoS: between 1936 and 1969, the number of records is practically equal in both indexes; between 1970 and 2001, the items from WoS exceed those from Scopus; and from 2002 onwards, the opposite occurs. Precisely, it is also from this period ahead

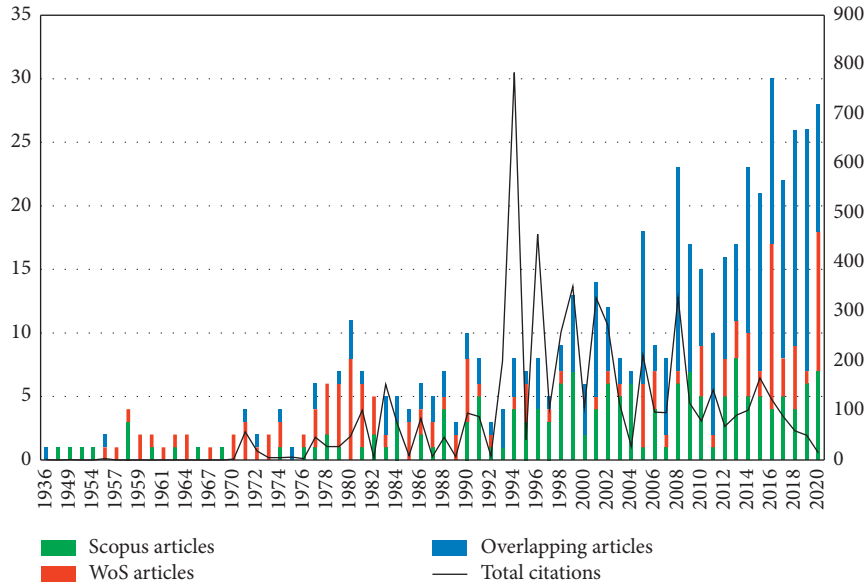

Figure 4: Research evolution based on Scopus and Web of Science database (1936–2020).

that there begins to be a more significant simultaneous presence of records in Scopus and WoS relating to the study of credit unions, mainly during the last years of the time horizon analyzed.

Table 2 compiles the ten journals with the highest number of citations, representing more than 50% of the citations contained in the records analyzed (5,801). First, a particularly significant fact can be detected: either over the entire period of analysis (Panel A, 1936–2020) or taking into account the two reference subperiods (Panel B, 1936–2004 and Panel C, 2005–2020), this group of publications is reduced to only 11 journals from three countries: the United Kingdom, Netherlands, and United States (with 8, 2, and 1 publication, respectively).

Similarly, no single journal can be said to dominate specifically in all the metrics employed: Journal of Economics and Business leads in the number of articles published, total citations and citations per year (1,185, 197.5, and 26.93, respectively); The Journal of Finance presents the highest SJR (18.151 (Q1)); Journal of Banking and Finance exhibits the highest h-index of the period (h-index = 13), and the Review of Social Economy has the longest longevity publishing topics related to credit unions (66 years).

For greater detail, it can be seen how the ranking of publications alters slightly depending on the subperiods of reference. In the 1936–2004 subperiod (Panel B), the three most relevant journals in terms of total citations are (in this order): Services Marketing Quarterly, Journal of Banking and Finance, and The Journal of Finance. However, in the 2005–2020 subperiod (Panel C), the ranking corresponds to (in this order): Journal of Banking and Finance, Annals of Public and Cooperative Economics, and Journal of Financial Services Research. In this regard, a quite significant pattern can be observed in both subperiods: curiously, the journals that top the rankings of total citations in each subperiod (Services Marketing Quarterly, and Journal of Banking and Finance) are those that have the least longevity presenting in the literature works focused on financial cooperativism (12 and 8 years, respectively).

Table 3 lists the most prolific countries in research on the credit union phenomenon. It can be seen that three countries lead the bibliographic production in this field throughout the period and subperiods defined: United States, United Kingdom, and Australia being precisely these countries, in that order, the ones with the highest number of authors and contributors. United Kingdom is the nation that usually presents the highest number of citations per author, except for Italy (Panel A, 1936–2020), which exhibits relatively high figures (31.57), starting from a relatively low number of authors (7). Once again, the United States, United Kingdom, and Australia are present in almost all the collaborative networks formed, while these networks are usually composed of nations with socio-cultural solid relations (e.g., France-Canada, Brazil-Portugal, United States-Canada-United Kingdom-Australia), or geographical proximity (e.g., Brazil-Ecuador).

Although most of the contributions come from the Anglo-Saxon area, some "newcomers" in financial cooperativism, such as Vietnam or Brunei, can also be found in the table, given the global dimension of the research. In this sense, Figure 5 outlines the network of clusters derived from the cooccurrence relationships that have emerged between the different countries that have contributed to the bibliographical production of credit unions over the 1936–2020 time horizon. Among them, the most representative cluster is the one formed by the United States, Cameroon, India, Japan, Nepal, and Uganda (red colour), followed by other groups formed by: Brazil, Chile, Ecuador, and Portugal (green colour), United Kingdom, Cyprus, Greece, and New Zealand (blue colour), Germany, South Africa, Switzerland, and Vietnam (yellow colour), Canada, China, and France (purple colour), Belgium, Denmark, and Ethiopia (light blue

Table 2: The most productive journals.

Panel A: The top 10 most productive journals in the period 1936–2020									
Journal	A	C	TC	TC/A	1st A	Last A	TC/Y	SJR(Q)	h-index
Annals of Public and Cooperative Economics	27	United Kingdom	250	9.26	1974	2020	5.32	0.526 (Q2)	9
Journal of Banking and Finance	18	Netherlands	890	49.44	1980	2016	21.71	1.580 (Q1)	13
Applied Economics	11	United Kingdom	145	13.18	1972	2020	2.96	0.569 (Q2)	8
Services Marketing Quarterly	7	United Kingdom	56	8.00	1986	1998	3.73	0.299 (Q3)	2
Managerial Finance	7	United Kingdom	68	9.71	2001	2018	6.80	0.271 (Q3)	5
Review of Social Economy	7	United Kingdom	124	17.71	1949	2015	1.72	0.281 (Q3)	6
The Journal of Finance	7	United Kingdom	269	38.43	1956	1984	4.14	18.151 (Q1)	5
Journal of Economics and Business	6	United States	1185	197.50	1977	2017	26.93	0.636 (Q1)	6
Journal of Financial Services Research	6	Netherlands	124	20.67	2000	2016	11.27	0.860 (Q1)	6
Public Money and Management	6	United Kingdom	77	12.83	2003	2020	9.63	0.492 (Q2)	4
Panel B: The top 5 most productive journals in the period 1936–2004									
Journal	A	C	TC	TC/A	1st A	Last A	TC/Y	SJR(Q)	h-index
Journal of Banking and Finance	12	Netherlands	650	54.17	1980	2002	15.85	1.580 (Q1)	8
Applied Economics	9	United Kingdom	127	14.11	1979	2003	3.02	0.569 (Q2)	8
Services Marketing Quarterly	7	United Kingdom	935	133.57	1986	1998	26.71	0.299 (Q3)	7
The Journal of Finance	7	United Kingdom	269	38.43	1956	1984	4.14	18.151 (Q1)	5
Annals of Public and Cooperative Economics	6	United Kingdom	64	10.67	1974	2004	1.36	0.526 (Q2)	4
Review of Social Economy	6	United Kingdom	115	19.17	1949	1996	1.60	0.281 (Q3)	5
Panel C: The top 5 most productive journals in the period 2005–2020									
Journal	A	C	TC	TC/A	1st A	Last A	TC/Y	SJR(Q)	h-index
Annals of Public and Cooperative Economics	21	United Kingdom	186	8.86	2005	2020	11.63	0.526 (Q2)	8
Journal of Banking and Finance	6	Netherlands	240	40.00	2008	2016	20.00	1.580 (Q1)	5
Managerial Finance	6	United Kingdom	53	8.83	2005	2018	3.31	0.271 (Q3)	4
Public Money and Management	5	United Kingdom	56	11.20	2007	2020	4.31	0.492 (Q2)	3
Enterprise Development and Microfinance	4	United Kingdom	36	9.00	2009	2020	3.00	0.209 (Q3)	3
Journal of Financial Services Research	4	Netherlands	89	22.25	2005	2016	6.36	0.860 (Q1)	4

A: number of articles; C: country; T.C: total citations; TC/A: total citations by article; 1st A: year corresponding to first published article; Last A: year corresponding to last published article; TC/Y: average number of citations per year since the 1st published article; SJR(Q) : SCImago Journal Rank (Quartile in 2020); h-index: Hirsch in this topic. Source: own elaboration.

Table 3: The most productive countries and main collaborators.

Panel A: The top 10 most productive countries in the period 1936–2020					
Country	A	TC	TC/A	NC	Main collaborators
United States	134	2,249	16.78	14	Canada, United Kingdom, Australia
United Kingdom	75	1,407	18.76	13	United States, Canada, Australia
Australia	33	406	12.30	5	United States, United Kingdom, Brazil
Canada	21	170	8.10	5	United States, United Kingdom, France
Brazil	16	51	3.19	3	Australia, Ecuador, Portugal
Ireland	13	128	9.85	2	United Kingdom, Brunei
China	12	49	4.08	1	Canada
Germany	7	24	3.42	3	United Kingdom, Switzerland, Vietnam
Italy	7	221	31.57	2	United Kingdom, Finland
France	6	42	7.00	1	Canada
Panel B: The top 5 most productive countries in the period 1936–2004					
Country	A	TC	TC/A	NC	Main collaborators
United States	74	1878	25.39	5	United Kingdom, Canada, Belgium
United Kingdom	26	819	31.50	4	United States, Ireland, Brunei
Australia	16	238	14.88	0	
Canada	6	43	7.17	1	United States
Ireland	4	30	7.50	2	United Kingdom, Brunei
Panel C: The top 5 most productive countries in the period 2005–2020					
Country	A	TC	TC/A	NC	Main collaborators
United States	60	371	6.18	11	Canada, United Kingdom, Australia
United Kingdom	49	588	12.00	11	United States, Canada, Australia
Australia	17	168	9.88	5	United Kingdom, United States, Brazil
Brazil	16	51	3.19	3	Australia, Ecuador, Portugal
Canada	15	127	8.47	5	France, United States, United Kingdom

A: number of articles, T.C: number of citations; TC/A: citations by article; NC: number of collaborators. Source: own elaboration.

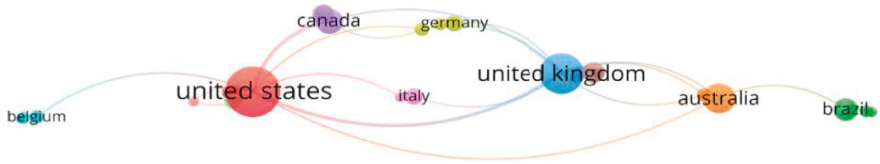

Figure 5: Network of cooperation based on authorship between countries (1936–2020).

Table 4: The top 10 most productive authors.

Panel A: The top 10 most productive authors in the period 1936–2020									
Author	A	TC	TC/A	1st A	Last A	TC/Y	h-index	Country	Affiliation
Mckillop D.	34	701	20.62	1995	2017	26.96	15	United Kingdom	Queen's University Belfast
Wilson J.O.S.	14	441	31.50	2002	2016	23.21	11	United Kingdom	University of St Andrews
Goddard J.	9	293	32.56	2002	2016	15.42	7	United Kingdom	Bangor University
Ward A.M.	9	130	14.44	2005	2014	8.13	8	United Kingdom	Queen's University Belfast
Ferguson C.	8	139	17.38	1995	2003	5.35	7	United Kingdom	University of Ulster
Ryder N.	7	34	4.86	2002	2009	1.79	4	United Kingdom	University of the West of England Bristol
Taylor R.A.	7	104	14.86	1971	1979	2.08	5	United States	Northern Illinois University
Glass J.C.	5	107	21.4	2002	2014	5.10	5	United Kingdom	University of Ulster
Kohers T.	5	31	6.20	1986	1990	0.89	2	United States	Mississippi State University
Mathuva D.M.	5	38	7.60	2015	2018	6.33	4	Kenya	Strathmore University
Mullis D.	5	31	6.20	1986	1990	0.86	2	United States	University of North Carolina at Charlotte
Panel B: The top 5 most productive authors in the period 1936–2004									
Author	A	TC	TC/A	1st A	Last A	TC/Y	h-index	Country	Affiliation
Mckillop D.	11	229	20.82	1995	2004	8.81	8	United Kingdom	Queen's University Belfast
Ferguson C.	8	139	17.38	1995	2003	5.35	7	United Kingdom	University of Ulster
Taylor R.A.	7	104	14.86	1971	1979	2.08	5	United States	Northern Illinois University
Kohers T.	5	31	6.20	1986	1990	0.89	2	United States	Mississippi State University
Mullis D.	5	31	6.20	1986	1990	0.86	2	United States	University of North Carolina at Charlotte
Panel C: The top 5 most productive authors in the period 2005–2020									
Author	A	TC	TC/A	1st A	Last A	TC/Y	h-index	Country	Affiliation
Mckillop D.	23	472	20.52	2005	2017	29.50	12	United Kingdom	Queen's University Belfast
Wilson J.O.S.	12	353	29.42	2005	2016	70.60	9	United Kingdom	University of St Andrews
Khafagy A.	9	7	0.78	2017	2020	1.75	1	Germany	Ruhr University of Bochum
Ward A.M.	9	130	14.44	2005	2014	8.13	8	United Kingdom	Queen's University Belfast
Goddard J.	8	226	28.25	2005	2016	14.13	6	United Kingdom	Bangor University

A: number of articles; T.C: total citations; TC/A: total citations by article; 1st A: year corresponding to first published article; Last A: year corresponding to last published article; TC/Y: average number of citations per year since the 1st published article; h-index: Hirsch in this topic. Source: own elaboration.

colour), Australia, Netherlands, and Thailand (orange colour), Ireland and Brunei (brown colour), and Italy and Finland (pink colour).

Table 4 lists the top ten most productive authors in the field of credit unions. First, there is a common denominator among these authors: their origin. These authors come from only four countries: the United Kingdom and the United States (mainly) and, to a lesser extent, Germany and Kenya. The preeminence of authors of British origin is quite representative, given that with 1,845 citations, they represent more than 30% of the total. Similarly, these researchers come from practically the same university centres. Again, the UK-based institutions predominate, reduced to 5: Queen's University Belfast, University of St Andrews, Bangor University, University of Ulster, and the University of the West of England Bristol. All of these universities are near each other and, except for the last one, they are located in central-northwest England, Wales, Scotland, and Northern Ireland.

Another aspect to consider is that these universities are quite close to Rochdale, the cradle of the cooperative movement. To a certain extent, the abundance of research in these universities could be due to the strong roots of the historical legacy of cooperativism in this zone of the planet. As far as North American universities are concerned, Northern Illinois University and Mississippi State University are located in rural areas of the United States (DeKalb and Starkville, respectively). The two regions have a strong presence of agrarian cooperativism arising from the cultivation of corn and cotton.

Focusing on the specific contributions of the authors, McKillop D. is undoubtedly the most prolific author, given that he shows the greatest bibliographic production, citations, citations per year, and h-index (34 articles, 701 citations, 20.62 citations per year, and h-index = 15). McKillop D. is followed in the ranking (in this order) by the following authors, who have frequently collaborated in his contributions: Wilson J.O.S., Goddard J., Ward A.M., and Ferguson C. (all from British universities). Note how McKillop D. leads the ranking throughout the period (Panel A) and subperiods analyzed (Panel B and Panel C), while several of

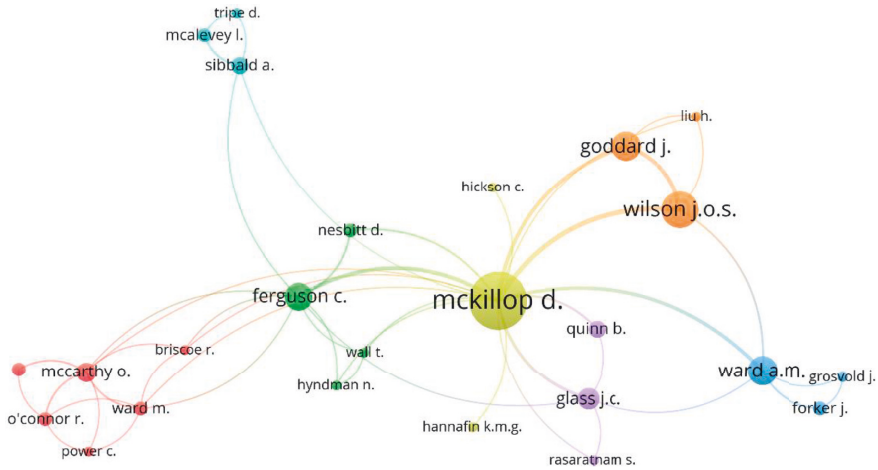

Figure 6: Network of cooperation based on coauthorship of the leading authors in the period 1936–2020.

the three authors indicated always accompany him in the first positions.

Concerning the clustering of the relationships between authors-collaborators arising from the bibliographic production related to credit unions, Figure 6 represents it, assigning a specific colour to each cluster. In this way, the following collaborative groups are defined: Hannafin KMG, Hickson C, and McKillop D (yellow colour), Goddard J, Liu H, and Wilson JOS (orange colour), Ferguson C, Hyndman N, Nesbitt D, and Wall T (green colour), Glass JC, Quinn B, and Rasaratnam S (purple colour), Mcalevey I, Sibbald A, and Tripe D (light blue colour), Briscoe R, Byrne N, McCarthy O, O'Connor R, Power C, and Ward M (red colour), and Forker J, Grosvold J, and Ward AM (blue colour).

Table 5 shows the most cited articles according to two subperiods: 1936–2004 (Panel A) and 2005–2020 (Panel B). First, it can be seen that there is no record before 1982 and that the oldest item according to this criterion is dated 1983 and corresponds to "Economies of Scale and Economies of Scope in Multiproduct Financial Institutions: A Study of British Columbia Credit Unions" [95]. Of the remaining records, eight were published during the 1990s (1990–2000) and eleven were published at the beginning of the millennium (2001–2011). Likewise, there is a certain dispersion in the journals in which the papers included in the ranking were published. A different journal published each article except for the Journal of Banking and Finance, including five papers.

The ranking in the subperiod 1936–2004 is headed by Barron , D.N. et al. [91, 106] with 14.19 and 13.52 citations per year, respectively, while in the subperiod 2005–2020 are [67, 87], with 10 and 6 citations per year, respectively. The multidisciplinarity and the different approaches from which the credit unions have been analyzed are evident in Table 5. In the subperiod 1936–2004 (Panel A), we can find lines of research related to economic history [47, 48], determination of the performance of these institutions [86], generation of economies of scale [95], or agricultural economics [74]. In the 2005–2020 subperiod (Panel B), the most cited articles focus on topics related to integration [88], diversification [87, 100], or poverty eradication [4, 78].

Figures 7 and 8 represent two strategic diagrams elaborated using SciMAT, taking as reference two measures for the realization of the clusters [44]: centrality and density. The former quantifies the interaction of a network to other networks, while the latter measures the degree of intensity of internal links within the cluster. Based on this preliminary arrangement, four types of themes can be identified: driving themes (first quadrant): developed themes, singularly important for the construction of the scientific field; peripheral themes (second quadrant): themes isolated from the rest, which have developed internally and play only a marginal role in the development of the scientific field; emerging or declining themes (third quadrant): poorly developed themes; and basic or transversal themes (fourth quadrant): themes important for the development of the scientific field, which lack previous development.

Thus, in the strategic diagram exhibited in Figure 7 (subperiod 1936–2004), the peripheral themes of this scientific field identified by the strategic diagram are Agricultural-credit, Commercial Bank, China, Credit-Cooperatives, Depository-institution-competition, Domestic-institution, and Household-savings. In the emerging or declining themes quadrant can be found: Banking-industry, Capital-flow, Cobb–Douglas, DEA, OECS-Country, and Nonradial, while in the core or cross-cutting themes quadrant, the following terms are listed: Asymmetric-information, Capital-provision, Credit unions, Customer-reduction, Gender-issues, Neoinstitutionalism, and Urban-Economy. Finally, the quadrant assigned to the driving themes of the research includes Artificial-intelligence, Article, Credit-access, Finance, Credit-provision, and Methodological-approach.

Following an analogous scheme, according to Figure 8 (subperiod 2005–2020), this scientific field's driving or important themes are: Article, Financial-Sustainability, and Credit-provision. Likewise, the peripheral themes indicated by the strategic diagram are Basel-III, Indonesia, Kenya, and Financial-Literacy. In the quadrant of emerging or declining

Table 5: The most cited articles.

Title	Author/s	Journal	TC	Year	TC/Year
Panel A: The top 10 most cited articles in the period 1936–2004					
A time to grow and a time to die: Growth and mortality of credit unions in New York City, 1914–1990	Barron D.N., West E, Hannan M.T.	American Journal of Sociology	383	1994	14.19
A comparison of neural networks and linear scoring models in the credit union environment	Desai V.S., Crook J.N., Overstreet G.A. Jr	European Journal of Operational Research	338	1996	13.52
Thy neighbor's keeper: The design of a credit cooperative with theory and a test	Banerjee A.V., Besley T., Guinnane T.W.	Quarterly Journal of Economics	245	1994	9.07
Availability and cost of credit for small businesses: Customer relationships and credit cooperatives	Angelini P., Di Salvo R., Ferri G.	Journal of Banking and Finance	199	1998	8.65
Evaluating the performance of US credit unions	Fried H.O., Knox Lovell C.A., Eeckaut P.V.	Journal of Banking and Finance	166	1993	6.15
Economies of scale and economies of scope in multiproduct financial institutions: A study of British Columbia credit unions	Murray J.D., White R.W.	The Journal of Finance	139	1983	3.66
Cooperatives as information machines: German rural credit cooperatives, 1883–1914	Guinnane T.W.	Journal of Economic History	125	2001	6.25
Credit-scoring models in the credit union environment using neural networks and genetic algorithms	Desai V.S., Conway D.G., Crook J.N., Overstreet G.A. Jr	IMA Journal of Management Mathematics	99	1997	4.13
A failed institutional transplant: Raiffeisen's credit cooperatives in Ireland, 1894–1914	Guinnane T.W.	Explorations in Economic History	93	1994	3.44
The role of groups and credit cooperatives in rural lending	Huppi M., Feder G.	World Bank Research Observer	70	1990	2.26
Panel B: The top 10 most cited articles in the period 2005–2020					
The diversification and financial performance of US credit unions	Goddard J., McKillop D., Wilson J.O.S.	Journal of Banking and Finance	130	2008	10.00
Credit unions: A theoretical and empirical overview	Mckillop D., Wilson J.O.S.	Financial Markets, Institutions and Instruments	60	2011	6.00
Firm operation performance analysis using data envelopment analysis and balanced scorecard: A case study of a credit cooperative bank	Chen T.-Y., Chen C.-B., Peng S.-Y.	International Journal of Productivity and Performance Management	43	2008	3.31
The power of networks: Integration and financial cooperative performance	Desrochers M., Fischer K.P.	Annals of Public and Cooperative Economics	41	2005	2.56
Diversification, fee income, and credit union risk	Esho N., Kofman P., Sharpe I.G.	Journal of Financial Services Research	35	2005	2.19
From tackling poverty to achieving financial inclusion:The changing role of British credit unions in low income communities	Jones P.A.	Journal of Socio-Economics	33	2008	2.54
Are credit unions too small?	Wheelock D.C., Wilson P.W.	Review of Economics and Statistics	33	2011	3.30
Irish credit unions: Investigating performance determinants and the opportunity cost of regulatory compliance	Glass J.C., McKillop D., Rasaratnam S.	Journal of Banking and Finance	28	2010	2.55
The development of credit unions and their role in tackling financial exclusion	McKillop D., Ward A.M., Wilson J.O.S.	Public Money and Management	28	2007	2.00
The effect of mergers on credit union performance	Bauer K., Miles L.L., Nishikawa T.	Journal of Banking and Finance	27	2009	2.25

TC: total citations; TC/Year: average number of citations per year since the article was published.

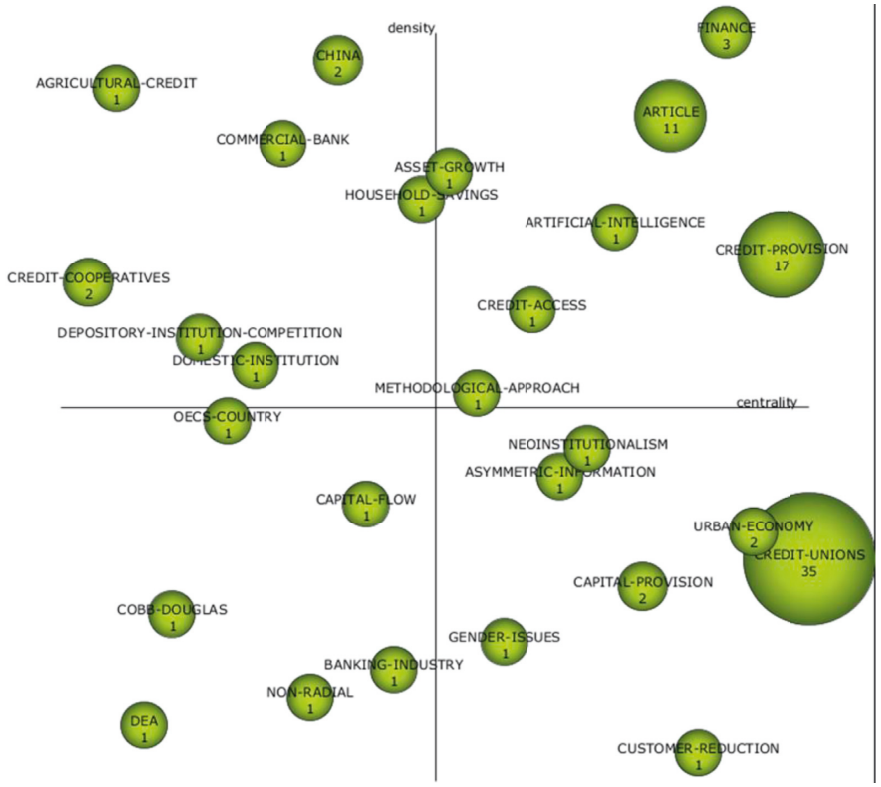

Figure 7: Strategic diagram of keywords from 1936–2004.

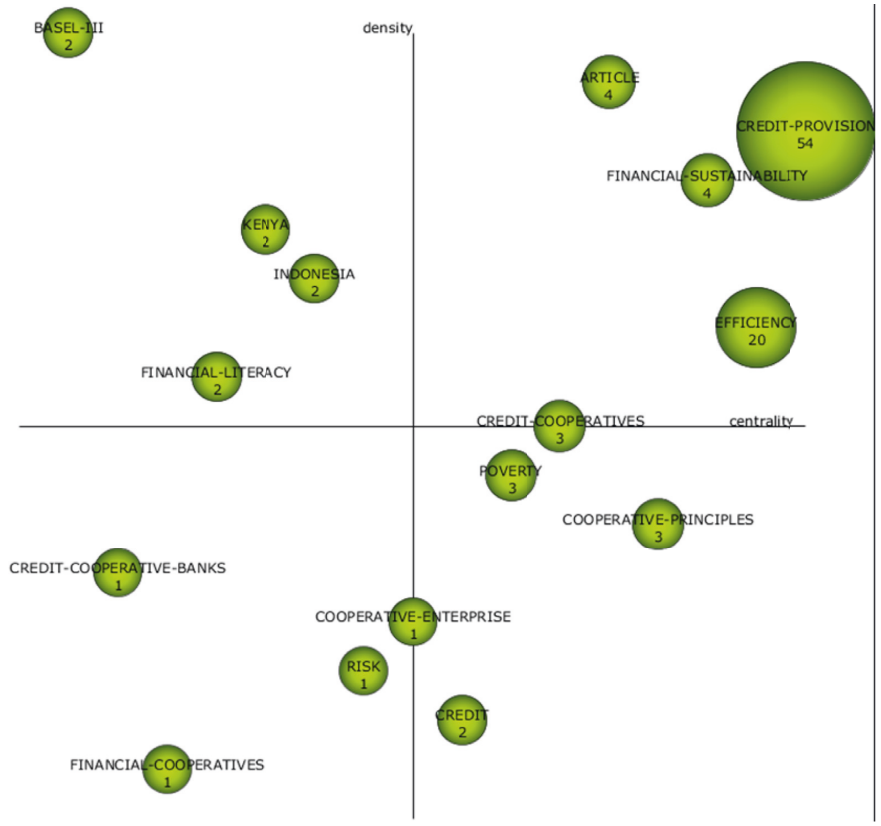

Figure 8: Strategic diagram of keywords from 2005–2020.

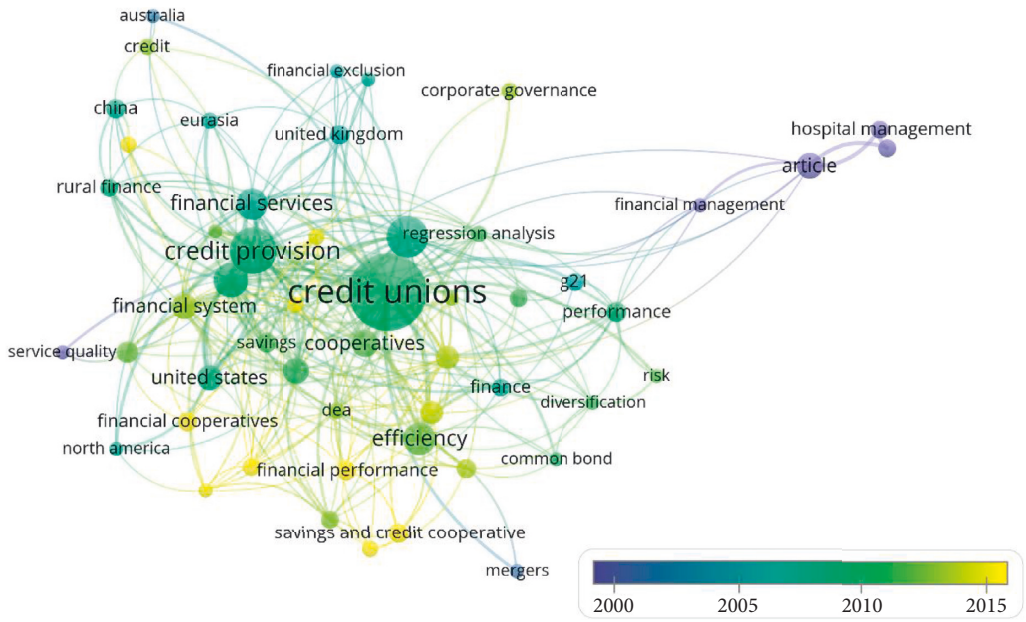

Figure 9: Evolution of leading keywords network based on cooccurrence (1936–2020).

themes are Credit-cooperative-banks, Cooperative-enterprise, Financial-cooperatives, and Risk and, subsequently, in the fourth quadrant (themes important for the development of the scientific field), three terms are located: Poverty, Cooperative-principles, and Credit.

Figure 9 complements the analysis of the most used keywords through the network visualization map based on the cooccurrence of keywords. The importance of each term analyzed is directly proportional to the "bubble" size in which it is included. As can be seen, appreciate credit unions leads the cluster, followed by other keywords such as credit provision, financial system, financial services, regression analysis, performance, efficiency, or saving cooperatives.

5. Conclusions

This study has carried out a bibliometric analysis of credit unions based on three keywords able to synthesize the main aspects of financial cooperativism: credit unions (*per se*), credit cooperatives, and financial cooperatives over almost a century, the period between 1936 and 2020. The Scopus and WoS databases have been used as representative indexes of the bibliographic analysis, detecting the common items present in both. Our research has used VOSviewer and SciMAT as joint bibliometric tools, which has allowed us to implement two types of analysis: content and descriptive. This research has resulted in a detailed dating of the main works published in the area, as well as the authors, countries, and university institutions of origin. In the same way, a mapping of the main collaborative networks that have emerged from the study of credit unions has been carried out based on two key elements: coauthorship of the principal authors and cross-country authorship.

On the other hand, the use of strategic diagrams oriented to the analysis of co-words based on a contrasted procedure such as Callon's co-word analysis [45, 124] has given rise to a taxonomy of the main terms according to the variables' density and centrality, describing the degree of relative importance of the main terms associated with financial cooperativism research. In this sense, the basic or transversal terms should guide future relevant lines of research in this area. We refer to lines of research related to the following terms: Asymmetric-information, Capital-provision, Cooperative-principles, Credit, Credit unions, Customer-reduction, Gender-issues, Neoinstitutionalism, Poverty, and Urban-Economy. Apart from these proposals, other recommendable lines of research would be to analyze monographically the new trends in rural cooperativism [125] or the implications of digitalization in credit unions [126]. Similarly, this field of research would be enriched by a bibliometric analysis of the impact of COVID-19 in the area of credit unions [126, 127]. The pandemic in 2019 has had a global impact on all human activities and areas of knowledge. Still, given its recent appearance, it is foreseeable that the specialized literature will consider the impact of the effects of COVID-19 on financial cooperativism.

Among the findings of this research, its dual nature should be highlighted. Indeed, it has become evident that the study of credit unions is a global, multidisciplinary phenomenon that encompasses different domains of knowledge (economics, finance, history, philosophy, politics, etc.). However, the prominent authors, contributions, and shared knowledge networks come from the United States and the United Kingdom. More specifically, we have been able to ascertain that most of the bibliographical production analyzed comes from areas relatively close geographically (Scotland, Wales, Northern Ireland, and central-northwest England), also very close to Rochdale, the historical epicentre of the cooperative financial movement. Hence, the existence of a certain "British School" in the study of credit unions formed by renowned authors such as McKillop D., Wilson J.O.S., Goddard J., Ward A.M., or Ferguson C. (who

have the highest number of articles, citations, and citations per year, as well as the highest h-index). Regarding the bibliographic evolution of the most representative publications, our findings show that Annals of Public and Cooperative Economics is the publication with the highest number of articles, followed by the Journal of Banking and Finance (which has the highest h-index of all the publications analyzed). In turn, The Journal of Finance represents the journal with the highest SJR(Q), with another publication, the Journal of Economics and Business, showing the highest number of total citations and citations per year and author.

In the light of the results obtained in this research, the implications and policies that can be established in practice are quite noticeable. This paper shows a joint perspective of the main characterizing facts of the cooperative movement, allowing us to obtain an accurate picture of its contribution to the well-being of society and its commitment to the neediest communities. A first practical implication of this study arises from verifying how the cooperativism of the Rochdale Pioneers was a movement that was born with a handicap: in fact, in the same way, that they advocated for the equality of all human beings, there was the curious paradox that women did not have the right to vote. Therefore, following McKillop's thesis [128], our research confirms that female emancipation would not be effective without the support of the credit unions.

If in practice, two major schools of research have investigated this movement (the United Kingdom and the United States versus France and Canada), everything seems to indicate that, consubstantially, both groups have studied the financial cooperativism according to the two main types of financial systems, continental and Anglo-Saxon, although the beneficial action of the credit unions can probably be considered as a response to the crisis of the latter [129]. In the same way, our research shows that cooperativism is an entirely global phenomenon that gathers multiple points of view depending on the needs of each country or specific area. Indeed, this paper contributes to summarize the main characteristics of financial cooperativism, without forgetting the nature of each society in which it is implemented. In other words, this bibliometric research has yielded the required results to compare the morphology of Western cooperativism versus other historical movements in other countries as is the case of Turkey [130, 131], which dates back to 1863. The strong linkage of financial cooperatives with Islamic Banking and Finance has been underlined [19], therefore and again in practice, public authorities have to facilitate the creation of Islamic credit cooperatives such as Al Barakah Multi-purpose Co-operative given that it is somewhat ironic that Islamic banking is becoming more and more popular in non-Islamic countries, while in several Islamic countries like Mauritius there is still a long way to go [132], whilst initiatives such as "Halal tourism" are starting to be successfully implemented.

From the bibliometric analysis, we have been able to verify how one of the fundamental roles of credit unions is to serve as a transmitter of microcredits towards the most disadvantaged sectors both in urban and rural areas of any country, whether developed or underdeveloped. Therefore, in the latter case, public authorities and supranational organizations must do everything possible to ensure that credit flows freely and not at a much higher cost than in developed countries, as is usually the case [133]. In the light of our work, credit unions must have a sufficiently flexible and dynamic organizational structure to cope with any problems that may arise, as demonstrated by the recent Ukrainian war crisis in which the reconstruction of this country would have been virtually impossible [134] without the measures, mechanisms, and projects that are analyzed in this bibliometric research.

The main limitation that we have encountered when carrying out this research is not a bibliometric impediment *per se* but is the very nature of the subject analyzed, the credit unions. By carrying out an exhaustive bibliometric analysis, it has been possible to determine at a global level the main distinctive features in the study of these societies based on their bibliographical production. However, it cannot be said that there is a homogeneous concept of the term that can be extrapolated to all nations and cultures. In other words, a corporate entity considered as a credit union in one country may not necessarily be regarded as such in another, and *vice versa*. This fact is because the regulation of credit unions is quite heterogeneous from one country to another, despite the efforts made by WOCCU [135].

Consequently, the lack of absolute harmonization of the term due to how each country regulates the legal and economic spheres of these organizations [8] constitutes a limitation of this study. The same consideration could be made concerning the overall values of each society. Credit unions are widespread worldwide, but there is no full equivalence of values at the global level either. The term "non-profit," which is so closely linked to these financial institutions, sometimes depends on the cultural relativism of policymakers [136], another element that makes it challenging to analyze credit unions from a univocal perspective.

Data Availability

The data correspond to Scopus and Web of Science, which are publicly available.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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References

[1] R. A. Taylor, "The Credit Union as a Cooperative Institution," *Review of Social Economy*, vol. 29, no. 2, pp. 207–217, 1971.

[2] D. C. Richardson, *Model Credit Unions into the Twenty-First*, G. D. Westley and B. Branch, Eds., Inter-American Development Bank and the World Council of Credit Unions, Washington, D.C, 2000.

[3] C. E. Cuevas, *The Relevance and Challenges of Credit Unions Today*, G. D. Westley and B. Branch, Eds., Inter-American Development Bank and the World Council of Credit Unions, Washington, D.C, 2000.

[4] D. G. McKillop, A.-M. Ward, and J. O. S. Wilson, "The development of credit unions and their role in tackling financial exclusion," *Public Money & Management*, vol. 27, no. 1, pp. 37–44, 2007.

[5] C. Dunford, "Credit unions and rural banks reaching down and out to the rural poor through group-based microfinance," *Enterprise Development & Microfinance*, vol. 20, no. 2, pp. 107–124, 2009.

[6] E. C. Johnson, "Rural cooperative credit unions," *Journal of Farm Economics*, vol. 18, no. 4, pp. 662–672, 1936.

[7] M. T. Vaziri, "Islamic finance, rural cooperative financial institutions (credit unions) and micro financing strategies," *Investment Management and Financial Innovations*, vol. 3, 2017.

[8] J. T. Croteau, "The credit union: legal form versus economic function," *Review of Social Economy*, vol. 7, no. 2, pp. 10–28, 1949.

[9] M. C. Walker and G. G. Chandler, "On the allocation of the net monetary benefits of credit union membership," *Review of Social Economy*, vol. 35, no. 2, pp. 159–168, 1977.

[10] B. P. Keating and M. O. Keating, "A managerial discretion theory of the nonprofit firm: an economic model of a credit union," *Journal of Business Research*, vol. 3, no. 4, pp. 345–354, 1975.

[11] J. T. Croteau, "The large credit union," *The Journal of Finance*, vol. 11, no. 3, pp. 347–362, 1956.

[12] R. A. Taylor, "Economies of scale in large credit unions," *Applied Economics*, vol. 4, no. 1, pp. 33–40, 1972.

[13] R. A. Taylor, "The demand for credit union shares: a cross-sectional analysis," *Journal of Financial and Quantitative Analysis*, vol. 7, no. 3, p. 1749, 1972.

[14] J.-P. D. Chateau, "The demand for and supply of deposits by credit unions," *Journal of Banking & Finance*, vol. 4, no. 2, pp. 151–173, 1980.

[15] T. P. Christopoulos and L. Gonzalez, "Achieving family farmers' demands for microcredit through credit unions: a framework for discussion," *RAM. Revista de Administração Mackenzie*, vol. 18, no. 5, pp. 116–143, 2017.

[16] WOCCU, "Advocating for Financial Cooperatives: Limiting Regulatory Burden at the Global Level," https://www.woccu.org/international_advocacy.

[17] R. Achwan, "The fountain of love credit union: a vibrant microfinance institution in a hostile inter-ethnic society," *Asian Case Research Journal*, vol. 16, no. 01, pp. 93–114, 2012.

[18] S. Dodaro and L. Pluta, "Big picture: the antigonish movement of eastern nova scotia,"*McGill-ueen's Studies in the History of Religion*, vol. 2, McGill-ueen's University Press, Montreal, 2012.

[19] M. R. N. Mohomed, "Islamic credit union: an inclusive financial institution to meet the needs of the community," *COMSATS Journal of Islamic Finance*, vol. 1, pp. 57–72, 2016.

[20] M. d. C. Valls Martínez, P. A. Martín-Cervantes, and S. Peña Rodríguez, "Ethical banking and poverty alleviation banking: the two sides of the same solidary coin," *Sustainability*, vol. 13, no. 21, p. 11977, 2021.

[21] WOCCU, Statistical Report, 2020.

[22] J. A. Senso and A. d. l. Rosa Piñero, "El concepto de metadato: algo más que descripción de recursos electrónicos," *Ciência da Informação*, vol. 32, no. 2, pp. 95–106, 2003.

[23] J. A. Moral-Muñoz, E. Herrera-Viedma, A. Santisteban-Espejo, and M. J. Cobo, "Software tools for conducting bibliometric analysis in science: an up-to-Date review," *El Profesional de la Información*, vol. 29, no. 1, 2020.

[24] O. N. Patiño Toro, Y. A. Correa, A. Valencia-Arias, and M. Benjumea-Arias, "A bibliometric analysis of the use of open source software in educational contexts," *Problems of Education in the 21st Century*, vol. 78, no. 1, pp. 114–128, 2020.

[25] O. Persson, R. Danell, and J. W. Schneider, "How to use bibexcel for various types of bibliometric analysis," in *Celebrating Scholarly Communication Studies: A Festschrift for Olle Persson at His 60th Birthday*, F. Åström, R. Danell, B. Larsen, and J. W. Schneider, Eds., pp. 9–24, International Society for Scientometrics and Informetrics, Leuven, 2009.

[26] M. Aria and C. B. Cuccurullo, "Bibliometrix: an R-tool for comprehensive science mapping analysis," *Journal of Informetrics*, vol. 11, no. 4, pp. 959–975, 2017.

[27] C. Chen, "Searching for intellectual turning points: progressive knowledge domain visualization," *Proceedings of the National Academy of Sciences*, vol. 101, no. suppl_1, pp. 5303–5310, 2004.

[28] L. Leydesdorff, A. Thor, and L. Bornmann, "Further steps in integrating the platforms of WoS and Scopus: historiography with HistCite and main-path analysis," *El Profesional de la Información*, vol. 26, no. 4, p. 662, 2017.

[29] S. H. H. Shah, S. Lei, M. Ali, D. Doronin, and S. T. Hussain, "Prosumption: bibliometric analysis using HistCite and VOSviewer," *Kybernetes*, no. ahead-of-print, pp. 1020–1045, 2019.

[30] S. P. Borgatti, *NetDraw Software for Network Visualization*, Analytic Technologies, Lexington, 2002.

[31] NWB Team, *Network Workbench Tool*, Indiana University, Northeastern University, and University of Michigan, 2006.

[32] V. Batagelj and A. Mrvar, "Pajek - analysis and visualization of large networks," in *Graph Drawing Software. Mathematics and Visualization*, M. Jünger and P. Mutzel, Eds., Springer, Berlin-Heidelberg, 2004.

[33] H. A. Schildt and J. T. Mattsson, "A dense network subgrouping algorithm for co-citation analysis and its implementation in the software tool Sitkis," *Scientometrics*, vol. 67, no. 1, pp. 143–163, 2006.

[34] S. P. Borgatti, M. G. Everett, and L. C. Freeman, *Ucinet for Windows: Software for Social Network Analysis*, Analytic Technologies, Harvard, 2002.

[35] I. Rafols, A. L. Porter, and L. Leydesdorff, "Science overlay maps: a new tool for research policy and library management," *Journal of the American Society for Information Science and Technology*, vol. 61, no. 9, pp. 1871–1887, 2010.

[36] N. J. Van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, 2010.

[37] C. Martín and M. J. SciMat, *Herramienta Software Para El Análisis de La Evolución Del Conocimiento Científico*, Propuesta de Una Metodología de Evaluación, University of Granada, Spain, 2012.

[38] N. J. Van Eck and L. Waltman, "Bibliometric mapping of the computational intelligence field," *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 15, no. 5, pp. 625–645, 2007.

[39] N. J. Van Eck and L. Waltman, "Visualizing bibliometric networks," in *Measuring Scholarly Impact*Springer, Cham, 2014.

[40] N. J. Van Eck, L. Waltman, R. Dekker, and J. van den Berg, "A comparison of two techniques for bibliometric mapping: multidimensional scaling and VOS," *Journal of the American Society for Information Science and Technology*, vol. 61, no. 12, pp. 2405–2416, 2010.

[41] L. Waltman and N. J. Van Eck, "A new methodology for constructing a publication-level classification system of science," *Journal of the American Society for Information Science and Technology*, vol. 63, no. 12, pp. 2378–2392, 2012.

[42] M. Cobo, A. G. López-Herrera, E. Herrera-Viedma, and F. Herrera, "SciMAT: a new science mapping analysis software tool," *Journal of the American Society for Information Science and Technology*, vol. 63, no. 8, pp. 1609–1630, 2012.

[43] M. Cobo, M. A. Martínez, M. Gutiérrez-Salcedo, H. Fujita, and E. Herrera-Viedma, "25 Years at knowledge-based systems: a bibliometric analysis," *Knowledge-Based Systems*, vol. 80, pp. 3–13, 2015.

[44] J.-R. López-Robles, J. Guallar, N.-K. Gamboa-Rosales, J. R. Otegi-Olaso, and M. J. Cobo Martín, "Mapa de La Estructura Intelectual de El Profesional de La Información de 2014 a 2018," *Hipertext. net*, pp. 115–125, 2019.

[45] M. Callon, J. P. Courtial, and F. Laville, "Co-word analysis as a tool for describing the network of interactions between basic and technological research: the case of polymer chemsitry," *Scientometrics*, vol. 22, no. 1, pp. 155–205, 1991.

[46] T. W. Guinnane, "A "friend and advisor": external auditing and confidence in Germany's credit cooperatives, 1889–1914," *Business History Review*, vol. 77, no. 2, pp. 235–264, 2003.

[47] T. W. Guinnane, "Cooperatives as information machines: German rural credit cooperatives, 1883-1914," *The Journal of Economic History*, vol. 61, no. 2, pp. S0022050701028042–S0022050701028389, 2001.

[48] T. W. Guinnane, "A failed institutional transplant: Raiffeisen's credit cooperatives in Ireland, 1894-1914," *Explorations in Economic History*, vol. 31, no. 1, pp. 38–61, 1994.

[49] P. Thomas and J. D. Wright, "Socialism," in *International Encyclopedia of the Social & Behavioral Sciences*, pp. 833–835, Elsevier, Amsterdam, Second Edition, 2015.

[50] S. A. Shaviro, "A critique of consumer cooperation: 'cheap cheese' or the heavenly kindgom as the issue that divides practical cooperators from utopians," *The American Journal of Economics and Sociology*, vol. 41, no. 1, pp. 29–42, 1982.

[51] P. Hibberd, "The Rochdale tradition in co-operative history is it justified?" *Annals of Public and Cooperative Economics*, vol. 39, no. 4, pp. 531–557, 1968.

[52] A.-M. Ward and D. G. Mckillop, "The law of proportionate effect: the growth of the UK credit union movement at national and regional level," *Journal of Business Finance & Accounting*, vol. 32, no. 9-10, pp. 1827–1859, 2005.

[53] A.-M. Ward and D. G. McKillop, "An investigation into the link between UK credit union characteristics, location and their success," *Annals of Public and Cooperative Economics*, vol. 76, no. 3, pp. 461–489, 2005.

[54] D. G. McKillop, J. Colin Glass, and A.-M. Ward, "Cost efficiency, environmental influences and UK credit unions, 1991 to 2001," *Managerial Finance*, vol. 31, no. 11, pp. 72–86, 2005.

[55] D. M. Mathuva, J. K. Mboya, and J. B. McFie, "Achieving legitimacy through Co-operative governance and social and environmental disclosure by credit unions in a developing country," *Journal of Applied Accounting Research*, vol. 18, no. 2, pp. 162–184, 2017.

[56] R. A. Taylor, "Credit unions and cooperative banking in developed and developing countries," *Annals of Public and Cooperative Economics*, vol. 45, no. 2, pp. 105–118, 1974.

[57] J. Bou Dib Lekocaj, J. Lekoçaj, and G. Van Dijk, "Cooperative microfinance in agriculture analyzing the outreach and financial sustainability of Albanian savings & credit union," *European Journal of Sustainable Development*, vol. 3, no. 4, pp. 29–36, 2014.

[58] A. Greinke, "Imposing capital controls on credit unions: an analysis of regulatory intervention in Australia," *Annals of Public and Cooperative Economics*, vol. 76, no. 3, pp. 437–460, 2005.

[59] F. Amersdorffer, G. Buchenrieder, R. Bokusheva, and A. Wolz, "Efficiency in microfinance: financial and social performance of agricultural credit cooperatives in Bulgaria," *Journal of the Operational Research Society*, vol. 66, no. 1, pp. 57–65, 2015.

[60] N. Ojong, "Credit unions as conduits for microfinance delivery in Cameroon," *Annals of Public and Cooperative Economics*, vol. 85, no. 2, pp. 287–304, 2014.

[61] G. J. Duguma and J. Han, "Effect of deposit mobilization on the technical efficiency of rural saving and credit cooperatives: evidence from Ethiopia," *Annals of Public and Cooperative Economics*, vol. 92, no. 4, pp. 621–647, 2020.

[62] D. Jones and P. Kalmi, "Membership and performance in Finnish financial cooperatives: a new view of cooperatives?" *Review of Social Economy*, vol. 73, no. 3, pp. 283–309, 2015.

[63] J. C. Glass, D. G. McKillop, and S. Rasaratnam, "Irish credit unions: investigating performance determinants and the opportunity cost of regulatory compliance," *Journal of Banking & Finance*, vol. 34, no. 1, pp. 67–76, 2010.

[64] N. Yamori, K. Harimaya, and K. Tomimura, "The efficiency of Japanese financial cooperatives: an application of parametric distance functions," *Journal of Economics and Business*, vol. 94, pp. 43–53, 2017.

[65] T. M. J. Fullerton and E. P. Muñiz, "Credit union loan rate determinants in the United States," *Applied Economics*, vol. 52, no. 49, pp. 5413–5425, 2020.

[66] A. V. Banerjee, T. Besley, and T. W. Guinnane, "Thy neighbor's keeper: the design of a credit cooperative with theory and a test," *Quarterly Journal of Economics*, vol. 109, no. 2, pp. 491–515, 1994.

[67] D. G. Mckillop and J. O. S. Wilson, "Credit unions: a theoretical and empirical overview," *Financial Markets, Institutions & Instruments*, vol. 20, no. 3, pp. 79–123, 2011.

[68] D. J. Smith, T. F. Cargill, and R. A. Meyer, "An economic theory of a credit union," *The Journal of Finance*, vol. 36, no. 2, pp. 519–528, 1981.

[69] B. P. Keating and M. O. Keating, "An empirical estimation of the degree of expense preference behavior between credit unions by common bond type," *The Quarterly Review of Economics and Finance*, vol. 32, pp. 71–84, 1992.

[70] J. A. Goddard and J. O. S. Wilson, "US credit unions: an empirical investigation of size, age and growth," *Annals of Public and Cooperative Economics*, vol. 76, no. 3, pp. 375–406, 2005.

[71] D. J. Smith, "A theoretic framework for the analysis of credit union decision making," *The Journal of Finance*, vol. 39, no. 4, pp. 1155–1168, 1984.

[72] M. Y. A. Rawwas, A. F. Thompson, and J. Truke, "The business ethics of credit union managers: conflicts, practices

and beliefs," *Journal of Professional Services Marketing*, vol. 18, no. 2, pp. 39–57, 1998.

[73] H. Black and R. H. Dugger, "Credit union structure, growth and regulatory problems," *The Journal of Finance*, vol. 36, no. 2, pp. 529–538, 1981.

[74] M. Huppi and G. Feder, "The role of groups and credit cooperatives in rural lending," *The World Bank Research Observer*, vol. 5, no. 2, pp. 187–204, 1990.

[75] P. Cabo and J. Rebelo, "Why do agricultural credit cooperatives merge? The Portuguese experience," *Annals of Public and Cooperative Economics*, vol. 76, no. 3, pp. 491–516, 2005.

[76] M. B. Yunus, *To the Poor: Micro-lending and the Battle against World Poverty*, Hachette UK, London, 2007.

[77] N. J. Ryder, "Credit unions and financial exclusion – the odd couple?" *Journal of Social Welfare and Family Law*, vol. 24, no. 4, pp. 423–434, 2002.

[78] P. A. Jones, "From tackling poverty to achieving financial inclusion-the changing role of British credit unions in low income communities," *The Journal of Socio-Economics*, vol. 37, no. 6, pp. 2141–2154, 2008.

[79] P. McGregor, "Credit unions and the supply of insurance to low income households," *Annals of Public and Cooperative Economics*, vol. 76, no. 3, pp. 355–374, 2005.

[80] M. Yunus, *Three Farmers Of Jobra*, Chittagong University, Hathazari Upazila, 1974.

[81] M. Yunus, *Credit Is a Human Right*, Central Bank of Sri Lanka, Colombo, Occasional Papers, 1994.

[82] A. Khafagy, "Political institutions and financial cooperative development," *Journal of Institutional Economics*, vol. 13, no. 2, pp. 467–498, 2017.

[83] R. S. Koot and D. A. Walker, "A statistical analysis of the impact of monetary policy on credit union lending," *Journal of Banking & Finance*, vol. 4, no. 3, pp. 301–311, 1980.

[84] C. F. Goenner, "The policy impact of new rules for loan participation on credit union returns," *Journal of Banking & Finance*, vol. 73, pp. 198–210, 2016.

[85] R. M. Gyasi, D. R. Phillips, and A. M. Adam, "How far is inclusivity of financial services associated with food insecurity in later life? Implications for health policy and sustainable development Goals," *Journal of Applied Gerontology*, vol. 40, no. 2, pp. 189–200, 2021.

[86] H. O. Fried, C. A. Knox Lovell, and P. V. Eeckaut, "Evaluating the performance of US credit unions," *Journal of Banking & Finance*, vol. 17, no. 2-3, pp. 251–265, 1993.

[87] J. A. Goddard, D. G. McKillop, and J. O. S. Wilson, "The diversification and financial performance of US credit unions," *Journal of Banking & Finance*, vol. 32, no. 9, pp. 1836–1849, 2008.

[88] M. Desrochers and K. P. Fischer, "The power of networks: integration and financial cooperative performance," *Annals of Public and Cooperative Economics*, vol. 76, no. 3, pp. 307–354, 2005.

[89] T.-Y. Chen, C.-B. Chen, and S.-Y. Peng, "Firm operation performance analysis using data envelopment analysis and balanced scorecard: a case study of a credit cooperative bank," *International Journal of Productivity and Performance Management*, vol. 57, no. 7, pp. 523–539, 2008.

[90] K. J. Bauer, L. L. Miles, and T. Nishikawa, "The effect of mergers on credit union performance," *Journal of Banking & Finance*, vol. 33, no. 12, pp. 2267–2274, 2009.

[91] D. N. Barron, E. West, and M. T. Hannan, "A time to grow and a time to die: growth and mortality of credit unions in New York city, 1914-1990," *American Journal of Sociology*, vol. 100, no. 2, pp. 381–421, 1994.

[92] J. B. Mason and J. L. Lollar, "Developing market driven strategies for credit union growth and survival," *Services Marketing Quarterly*, vol. 2, no. 1, pp. 91–108, 1986.

[93] A. Serenko, N. Bontis, and E. Hull, "An application of the knowledge management maturity model: the case of credit unions," *Knowledge Management Research and Practice*, vol. 14, no. 3, pp. 338–352, 2014, –15.

[94] C. Ferguson and D. G. Mckillop, "Classifying credit union development in terms of mature, transition and nascent industry types," *Service Industries Journal*, vol. 20, no. 4, pp. 103–120, 2000.

[95] J. D. Murray and R. W. White, "Economies of scale and economies of Scope in Multiproduct financial institutions: a study of British Columbia credit unions," *The Journal of Finance*, vol. 38, no. 3, pp. 887–902, 1983.

[96] R. S. Koot, "On economies of scale in credit unions," *The Journal of Finance*, vol. 33, no. 4, pp. 1087–1094, 1978.

[97] T. Kohers and D. Mullis, "An update on economies of scale in credit unions," *Applied Economics*, vol. 20, no. 12, pp. 1653–1659, 1988.

[98] N. Esho, "Scale economies in credit unions: accounting for subsidies is important," *Journal of Financial Services Research*, vol. 18, no. 1, pp. 29–43, 2000.

[99] D. C. Wheelock and P. W. Wilson, "Are credit unions too small?" *The Review of Economics and Statistics*, vol. 93, no. 4, pp. 1343–1359, 2011.

[100] N. Esho, P. Kofman, and I. G. D. Sharpe, "Diversification, fee income, and credit union risk," *Journal of Financial Services Research*, vol. 27, no. 3, pp. 259–281, 2005.

[101] P. Angelini, R. Di Salvo, and G. Ferri, "Availability and cost of credit for small businesses: customer relationships and credit cooperatives," *Journal of Banking & Finance*, vol. 22, no. 6-8, pp. 925–954, 1998.

[102] E. Pana, S. Vitzthum, and D. Willis, "The impact of internet-based services on credit unions: a propensity score matching approach," *Review of Quantitative Finance and Accounting*, vol. 44, no. 2, pp. 329–352, 2015.

[103] K. Hayton, "The role of Scottish credit unions in tackling financial exclusion," *Policy & Politics*, vol. 29, no. 3, pp. 281–297, 2001.

[104] G. Dubauskas, "Sustainable growth of the financial sector: the case of credit unions," *Journal of Security and Sustainability Issues*, vol. 1, no. 3, pp. 159–166, 2012.

[105] V. S. Desai, D. G. Conway, J. N. Crook, and G. A. Overstreet Jr., "Credit-scoring models in the credit-union environment using neural networks and genetic algorithms," *IMA Journal of Management Mathematics*, vol. 8, no. 4, pp. 323–346, 1997.

[106] V. S. Desai, J. N. Crook, and G. A. Overstreet Jr., "A comparison of neural networks and linear scoring models in the credit union environment," *European Journal of Operational Research*, vol. 95, no. 1, pp. 24–37, 1996.

[107] M. J. Page, J. E. McKenzie, P. M. Bossuyt et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," *BMJ*, vol. 372, p. n71, 2021.

[108] J. W. do Prado, V. de Castro Alcântara, F. de Melo Carvalho, K. C. Vieira, L. K. C. Machado, and D. F. Tonelli, "Multivariate analysis of credit risk and bankruptcy research data: a bibliometric study involving different knowledge fields (1968–2014)," *Scientometrics*, vol. 106, no. 3, pp. 1007–1029, 2016.

[109] D. F. Costa, F. de Melo Carvalho, B. C. de Melo Moreira, and J. W. do Prado, "Bibliometric analysis on the association between behavioral finance and decision making with cognitive biases such as overconfidence, anchoring effect and

confirmation bias," *Scientometrics*, vol. 111, no. 3, pp. 1775–1799, 2017.
[110] S. C. Maia, G. C. de Benedicto, J. W. do Prado et al., "Mapping the literature on credit unions: a bibliometric investigation grounded in Scopus and Web of science," *Scientometrics*, vol. 120, no. 3, pp. 929–960, 2019.
[111] M. Gusenbauer and N. R. Haddaway, "Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources," *Research Synthesis Methods*, vol. 11, no. 2, pp. 181–217, 2020.
[112] Y. Gavel and L. Iselid, "Web of Science and Scopus: a journal title overlap study," *Online Information Review*, vol. 32, no. 1, pp. 8–21, 2008.
[113] P. Mongeon and A. Paul-Hus, "The journal coverage of Web of Science and Scopus: a comparative analysis," *Scientometrics*, vol. 106, no. 1, pp. 213–228, 2016.
[114] L. D. Filser, F. F. da Silva, O. J. de Oliveira, and O. J. State, "of research and future research tendencies in lean healthcare: A bibliometric analysis," *Scientometrics*, vol. 112, no. 2, pp. 799–816, 2017.
[115] M. Adusei, N. Adeleye, and A. Okafor, "Drivers of credit union penetration: An international analysis," *Managerial and Decision Economics*, vol. 42, no. 3, pp. 710–723, 2021.
[116] A. Perianes-Rodriguez, L. Waltman, and N. J. Van Eck, "Constructing bibliometric networks: A comparison between full and fractional counting," *Journal of Informetrics*, vol. 10, no. 4, pp. 1178–1195, 2016.
[117] J. E. Hirsch, "An index to quantify an individual's scientific research output," *Proceedings of the National Academy of Sciences*, vol. 102, no. 46, pp. 16569–16572, 2005.
[118] A. F. J. Van Raan, "Comparison of the Hirsch-index with standard bibliometric indicators and with peer judgment for 147 chemistry research groups," *Scientometrics*, vol. 67, no. 3, pp. 491–502, 2006.
[119] S. Alonso, F. J. Cabrerizo, E. Herrera-Viedma, and F. H.-I. Herrera, "A review focused in its variants, computation and standardization for different scientific fields," *J. Informetr.*, vol. 3, pp. 273–289, 2009.
[120] M. E. Falagas, V. D. Kouranos, R. Arencibia-Jorge, and D. E. Karageorgopoulos, "Comparison of SCImago journal Rank indicator with journal impact factor," *The FASEB Journal*, vol. 22, no. 8, pp. 2623–2628, 2008, https://doi.org/10.1096/fj.08-107938.
[121] T. F. Cargill, "Recent research on credit unions: a survey," *Journal of Economics and Business*, vol. 29, pp. 155–162, 1977.
[122] R. E. Jackson, "How the credit union serves Teachers," *The bulletin of the National Association of Secondary School Principals*, vol. 29, no. 128, pp. 83-84, 1945.
[123] J. T. Croteau, "The federal credit union system: A legislative history," *Social Security Bulletin*, vol. 19, pp. 10–17, 1956.
[124] M. Callon, J.-P. Courtial, W. A. Turner, and S. Bauin, "From translations to problematic networks: An introduction to Co-word analysis," *Social Science Information*, vol. 22, no. 2, pp. 191–235, 1983.
[125] N. Byrne, O. McCarthy, and R. O'Connor, "The development of new rural credit unions in Ireland within a context of service rationalization in rural areas," *Community Development Journal*, vol. 39, no. 4, pp. 401–412, 2004.
[126] M. Mwamadzingo, S. Kisonzo, and N. D. Chakanya, "Adapt and innovate: challenges and opportunities for trade unions amidst the COVID-19 pandemic and the recovery period," *Int. J. Labour Res.*vol. 10, pp. 107–123, 2021.
[127] E. Herrera-Viedma, J.-R. López-Robles, J. Guallar, and M. J. Cobo, "Global trends in coronavirus research at the time of Covid-19: A general bibliometric approach and content analysis using SciMAT," *El Profesional de la Información*, vol. 29, no. 3, pp. 1–20, 2020.
[128] D. G. McKillop, R. Briscoe, O. McCarthy, M. Ward, and C. Ferguson, "Irish Credit Unions: Exploring the Gender Mix," *Voluntas: International Journal of Voluntary and Nonprofit Organizations*, vol. 14, no. 3, pp. 339–358, 2003.
[129] S. Konzelmann, M. Fovargue-Davies, and G. Schnyder, "The faces of liberal capitalism: Anglo-Saxon banking systems in crisis?" *Cambridge Journal of Economics*, vol. 36, no. 2, pp. 495–524, 2012.
[130] G. Ozdemir, "Women's Cooperatives in Turkey," *Procedia - Social and Behavioral Sciences*, vol. 81, pp. 300–305, 2013.
[131] G. Kusek, M. Turker, S. Akdemir, and S. Hayran, "Structural characteristics of the agricultural sector in terms of access to agricultural credits in Turkey," *New Medicine*, vol. 16, p. 66, 2017.
[132] M. Kahf, "La finance islamique gagne du terrain en angleterre pourquoi pas Au maurice?".
[133] R. Rosenberg, A. Gonzalez, and S. Narain, "The New Moneylenders: Are ThePoor Being Exploited by High Microcredit Interest Rates?" *CGAP Ocassional Pap*, 2009.
[134] W. O. C. C. U. Ukraine, "How are cooperatives helping those affected?".
[135] D. Bierecki, "Legal status and development trends of credit unions in Polish law and its compliance with the WOCCU standards and the international cooperative principles," *Boletín de la Asociación Internacional de Derecho Cooperativo*, vol. 56, pp. 19–45, 2020.
[136] L. Bonatti, "Cultural relativism and ideological policy makers in a general equilibrium model with for-profit and non-profit enterprises," *Research in Economics*, vol. 62, pp. 1–15, 2008.

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Research Article

Dynamic Nonlinear Connectedness between the Financial Inclusion, Economic Growth, and China's Poverty Alleviation: Evidence from a Panel VAR Analysis

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Whether financial inclusion and economic growth can sustainably release poverty alleviation effects in long term has been the focus of academia and government sector. This article uses provincial panel data from 2004 to 2019 to examine the dynamic nonlinear connectedness between the financial inclusion, economic growth, income inequality, and poverty alleviation; the main objective is to reveal the direction and intensity of the long-term and short-term impact of each factor on poverty alleviation. By building a panel vector autoregression model (PVAR), the comparison analyses of national, eastern, central, and western sample groups verify the existence of dynamic nonlinear connectedness among the four variables. The study found that there is complex bidirectional causality between these variables, financial inclusion has the long-term impact on promoting poverty alleviation in China, the impact of economic growth is relatively weak, and income inequality has weakened the positive impact of financial inclusion on poverty alleviation. Through the analysis of impulse response function, variance decomposition, and time-varying nonparametric estimates in different economic regions, we find that the impact of financial inclusion on poverty alleviation presents a U-shaped characteristic, and the contribution of financial inclusion to poverty alleviation in western regions is significant, but poverty reduction in eastern and central region mainly depends on economic growth. For policymakers, financial inclusion can be an effective way to alleviate relative poverty, but the poverty governance should focus more on reducing income inequality in China.

1. Introduction

Poverty alleviation is the most important indicator in the Sustainable Development Goals (SDGs), which emphasize the need for a reduction of inequality and the eradication of global poverty in all forms by 2030 [1, 2]. As one of the most dynamic economies in the world, China has not only achieved sustained economic growth, but also achieved world-renowned achievements in poverty eradication. At the end of 2020, China successfully completed the arduous task of eliminating absolute poverty, and 98.99 million rural poor people were lifted out of poverty as scheduled, marking a comprehensive victory in the battle against poverty [3]. However, eradicating absolute poverty does not mean the end of antipoverty work. The relative poverty problem in China will still exist for a long time [4], and accidental factors from the economy, society, and family may also lead to the return of poverty-stricken people [5]. Therefore, consolidating existing achievements in poverty alleviation, especially establishing a long-term mechanism for poverty alleviation, has become the focus of theoretical circles and policymakers.

The scholars have put forward many opinions about the reasons for poverty alleviation, and many studies attribute it to sustained economic growth [6]. Some scholars regard financial development and economic growth as an

important way to eliminate poverty in developing countries based on neoclassical economics and development economics theory [7–10]. In terms of the impact mechanisms of financial development and economic growth on poverty alleviation, there are two representative views in the existing research. First, financial development has a "hematopoietic function." By providing financial support to production factors, the financial sector stimulates the actual output of production activities, and ultimately achieves increased employment opportunities and poverty alleviation [11]. Second, there is a "trickle-down effect" in economic growth. Economic growth can spontaneously increase the income of poor groups, and financial development narrows the income gap through the "trickle-down effect" of economic growth [12]; as such, the problem of poverty will eventually be eliminated with economic growth. Under the above-mentioned mechanism, financial poverty alleviation has become an important support for China's poverty alleviation strategy. After China's State Council's "Government Work Report" in 2015 proposed to vigorously develop financial inclusion [13], this financial poverty alleviation method has been advocated by research and practice [14, 15]. However, it is puzzling that some studies have found that in countries or regions with rapid financial development, income gaps and poverty are further aggravated [16, 17]. Some studies have also pointed out that when income gaps increase to offset the poverty alleviation effect of economic growth, economic growth will aggravate the degree of poverty, namely, the problem of "poverty growth" [18, 19]. In general, the poverty alleviation effect of financial inclusion and economic growth has not reached a conclusion, and it is not clear whether they can effectively and continuously promote poverty alleviation in the long term. How about the effect of financial inclusion and economic growth on poverty alleviation in China? What is the long-term and short-term dynamic evolution relationship between the development of financial inclusion, economic growth, and poverty alleviation? Furthermore, is the the dynamic impact consistent across different regions in China? In this context, an empirical analysis of the above issues is necessary, and the conclusions have important significance for the policy formulation of China's relative poverty. We use provincial panel data to build the PVAR model and examine the dynamic nonlinear impact of financial inclusion development and economic growth on poverty alleviation from the perspective of regional heterogeneity.

The contributions of this article are as follows. Firstly, an important point that has been ignored in previous literature is the lack of systematic consideration when examining the relationship between financial inclusion, economic growth, and poverty alleviation. Therefore, we put these economic variables into a systematic analysis framework based on poverty decomposition theory and focuses on the negative impact of income inequality. We find that increased income inequality offsets the poverty alleviation performance of financial inclusion and the finding can provide a new perspective for related research. Secondly, we analyze the dynamic impact effect between variables from nonlinear perspective, rather than the static impact from linear perspective in many studies, so that we more clearly understand the dynamic impact and duration of the interaction between variables. Furthermore, the bidirectional causality between economic variables is an unavoidable problem, and the PVAR model can avoid the impact of endogenous problems in the previous literature on the estimation results, which can provide a more accurate basis for policymakers to make poverty reduction policies. Finally, this article emphasizes the correct application of the PVAR analysis. In the last 20 years, the PVAR model has been widely used in economic research; however, there are still many authors who misuse this method. For example, the impulse response function analysis does not consider confidence intervals, and the conclusions also lack robustness check. Therefore, we hope to provide a standardized application case to provide reference for other scholars to use the PVAR model correctly in the future.

The remainder of the article is structured as follows. Section 2 is the literature review. Section 3 sets out the research materials and methods. Section 4 contains the results and discussion. Section 5 discusses the time-varying impact of financial inclusion on poverty alleviation using time-varying nonparametric estimation techniques. Finally, the research conclusions and policy implications of this study are summarized in Section 6.

2. Literature Review

Since the United Nations called for the establishment of a broad financial inclusion system in 2005, the concept of financial inclusion has spread rapidly around the world. Since then, research results on the relationship between financial inclusion, economic growth, and poverty alleviation have become more and more abundant, and both theoretical perspectives and research methods have gradually shown a trend of diversification. Through a literature review, it was found that the existing research on the abovementioned fields can be classified into four categories. The first relates to research on the impact of financial inclusion on poverty alleviation; the second is research on the relationship between economic growth and poverty alleviation; the third is research on the interactive relationship between financial inclusion and economic growth, and the four is the role of income inequality in economic growth and poverty alleviation. The details are as follows.

2.1. The Impact of Financial Inclusion on Poverty Alleviation. The impact of financial inclusion development on poverty alleviation has always been an important issue of concern to the academic community, but the role of financial inclusion development in poverty alleviation is far from reaching a consensus. Institutional factors are an important cause of poverty. Under the market economy system, the profit-seeking nature of capital exacerbates the polarization of income distribution [20]. Marx argued in Das Kapital that the increase of capital concentration puts the ownership and control of capital in the hands of a few people, so poverty and unemployment should be attributed to the capitalist system.

Even Keynesians believe that the shortcomings of the capitalist system include its failure to provide full employment and unequal distribution of wealth and income [21], and they regard monetary policy as an important means of macroeconomic regulation. Therefore, in order to solve the problem of poverty, it is important to consider the rational guidance of capital flow. In this view, financial development is often seen as an effective measure of addressing income inequality and poverty alleviation in developing countries [22]. Since the 1970s, in order to stimulate economic growth and poverty alleviation, governments of various countries have vigorously implemented financial deepening policies, which have generally improved the level of financial development [23]. Among many policies, financial inclusion plays a pivotal role in the process of poverty alleviation due to its advantage of enabling individuals and enterprises in the economy to easily access a wide range of financial services [24]. There has been a significant amount of scholarly research and discussion as to whether the development of financial inclusion can effectively alleviate poverty. On the one hand, there are many research results that support the development of financial inclusion to improve income levels and poverty alleviation. For example, Chibba [25] points out that countries need financial inclusion more urgently than ever before, because financial inclusion is a progressive program to achieve poverty alleviation and inclusive development. Sarma and Pais [26] also believe that financial inclusion includes the characteristics of convenience, availability, and effectiveness, which can help alleviate the poverty of low-income groups. In addition, more and more empirical studies have discussed the causal relationship between the development of financial inclusion and poverty alleviation; many studies have concluded that the development of financial inclusion can help achieve poverty alleviation, and its influencing mechanisms include the indirect effect of developing financial inclusion to stimulate economic growth, thereby narrowing the income gap, and the direct effect of broadening financial service channels [27–32]. On the other hand, there are also many economists who hold a negative attitude towards the poverty alleviation effect of financial inclusion. Critics argue that financial inclusion is nothing more than a "new coat" for microfinance, with questionable effectiveness when it comes to poverty alleviation in developing countries [33–35]. In other words, researchers challenge the traditional assumption of causality between financial inclusion, poverty alleviation, and income inequality. The reason for this is that due to the constraints of income level, professional knowledge and social status, the financial inclusion policy that can benefit most individuals in theory may still benefit high-income groups in practice, which leads to low-income groups being unable to enjoy equal financial service opportunities [36, 37].

2.2. The Relationship between Economic Growth and Poverty Alleviation. Since the 1990s, economists have paid more and more attention to the relationship between economic growth and poverty alleviation. Many studies show that economic growth helps to alleviate poverty in developing countries and regions, but the existing literature does not reach a consensus on the strength and direction of its impact [38]. From the perspective of the evolution of economic theory, neoclassical economics and the development economics theory constitute two important theoretical cornerstones in this field. On the one hand, based on the theory of diminishing marginal utility, neoclassical economics emphasizes the "trickle-down effect" of economic growth on low-income groups, arguing that economic growth can ultimately promote poverty alleviation in low-income groups in an effective way [38]. On the other hand, development economics suggests that due to the "vicious circle" between resource factors and economic growth, developing countries or regions fall into poverty and backwardness and are hard to get rid of, and the phenomenon of a "poverty trap" aggravates people's confusion in understanding the poverty alleviation effect of economic growth [39]. Therefore, researchers are constantly trying to find new theoretical explanations to reveal the internal mechanism of how economic growth affects poverty alleviation. For example, Zhong [40] explained the connection between economic growth and poverty alleviation from the perspective of resource allocation efficiency and pointed out that poverty alleviation is the result of economic growth, regional development, and targeted poverty alleviation led by the Chinese government. It is worth mentioning that some scholars have tried to explain the poverty alleviation effect of economic growth from the perspective of an economic growth model. Montalvo and Ravallion [41] first proposed the "economic growth model hypothesis," which holds that the sectoral or geographical composition of economic activities is independent, and the economic model will have an impact on the poverty alleviation effect of economic growth. In other words, the hypothesis attempts to answer the question of which model is more conducive to poverty alleviation between the balanced growth model and the nonequilibrium growth model of the economic sector. When discussing the impact of economic growth on poverty alleviation, Li and Bian [19] believe that the income distribution effect is greater than the economic growth effect. In terms of empirical research, although many studies suggest that economic growth has the role of promoting poverty alleviation, there are also critical voices in the existing literature. Based on the "poverty–growth–inequality" framework, proponents have verified that economic growth is the determinant of poverty alleviation [42, 43], and some studies have further explained the poverty alleviation mechanism of economic growth [44]. Some scholars have found that even with different poverty line standards, the economic growth elasticity of poverty alleviation is between −2 and −3, which means that 10% of economic growth will reduce poverty by 20% to 30% [45, 46]. At the same time, critics do not deny the poverty alleviation role of economic growth, but question the "trickle-down effect" of economic growth. Given that the empirical results do not fully support the conclusion that economic growth will benefit members of all income classes, the "trickle-down effect" of economic growth has been extensively criticized in theory and in reality [47]. In

addition, some scholars have put forward different views, suggesting that economic growth is not the only determinant of poverty alleviation [48], and the effectiveness of poverty alleviation may also be affected by the moderating effects of many factors such as policy, society, population, geography, and climate [49].

2.3. The Interactive Relationship between Financial Inclusion and Economic Growth. In the existing literature, it is evident that the interactive relationship between financial inclusion and economic growth has not been fully studied by the academic community. Most traditional financial development theories are based on the perspective of financial deepening, focusing on the comprehensive impact of financial intermediaries and financial markets on economic growth [12]. For example, when Schumpeter and Opie [50] discussed the theory of economic development, they emphasized the key role played by the financial system in the process of economic growth by stimulating innovation and productive financing. Scholars such as Lucas [51] and Miller [52] also agreed with this view; they put forward the theoretical proposition that financial markets contribute to economic growth and believe that if we want to promote economic growth, we should prioritize encouraging the rapid development of the financial sector. At the same time, King and Levine [53] pointed out that the financial sector is a stable capital intermediary system, and its capital availability can bring long-term economic growth and productivity improvement. The above studies all support the interactive relationship between financial development and economic growth. According to research by Siddik et al. [54], the economic growth effect of financial inclusion has received much attention in the last decade and is regarded as a priority policy option by central banks, regulators, and government officials. In this context, some of the literature regards the development of financial inclusion as an important engine and a key strategic component of sustained economic growth [55]. In addition, an increasing number of empirical studies also provide evidence of the interaction between financial inclusion and economic growth, but these studies show that there is not necessarily a positive influence between them. Some studies have confirmed that financial inclusion has a significant economic growth effect. For example, some scholars believe that the development of financial inclusion can help reduce transaction costs of microindividuals, alleviate the phenomenon of financial exclusion by traditional financial institutions, promote residents' intertemporal consumption by facilitating customer experience, and enhance the availability of capital to promote technological innovation and regional entrepreneurship, thus having a significant positive impact on economic growth [56–61]. Based on the perspective of cointegration theory, some scholars have also confirmed that there is a long-term stable equilibrium relationship between financial inclusion and economic growth and that there is a two-way causal relationship between them [62, 63]. However, when some scholars use econometric methods to analyze the economic growth effect of financial inclusion, they believe that the effect is negative or has no significance [64–66]. This is because in addition to the different definitions of financial inclusion, past studies have mostly focused on the linear effect or overall effect between financial inclusion and economic growth, ignoring the potential nonlinear effect or regional heterogeneity between them. As pointed out by Ali et al. [67], when exploring the economic impact of financial inclusion, it is necessary to include nonlinear effects or cross-group factors in the study, which can indicate the optimal strategy in different situations. When Li et al. [13] analyzed the economic growth effect of financial inclusion, they found that there was a significant positive impact in eastern China, but no significant impact in the central and western regions. Therefore, to explore the interactive relationship between financial inclusion and economic growth, we can try to conduct further in-depth analyses from the perspective of nonlinear effects or regional heterogeneity.

2.4. The Role of Income Inequality in Economic Growth and Poverty Alleviation. In addition to discussing the relationship between financial inclusion, economic growth, and poverty alleviation, many studies have also studied the impact of income inequality on economic growth and poverty alleviation performance. It is well known that income inequality and economic growth are usually regarded as exogenous shocks to an economy due to poverty. Inequality seems to be closely related to poverty, and scholars generally believe that it will have a negative impact on economic growth [68]. As pointed out in the literature by Bui et al. [69], the existence of inequality can undermine the effective implementation of policies, thereby hindering economic growth. In addition, widespread extreme income inequality is considered a huge threat to economic development, and poverty alleviation efforts in developing regions are slowing due to income inequality [70]. Its impact mechanism is that if the economic growth is accompanied by the widening of the income distribution gap, the poor groups will benefit from the growth less than the nonpoor groups, and the poverty alleviation effect of economic growth will be partially or completely offset by income inequality [71, 72]. Therefore, the World Bank has set a goal of ending extreme poverty by 2030 and improving the quality of life of the bottom 40 percent of people in every country by reducing income inequality. The question of how to solve the negative impact of income inequality on economic growth is a reality that governments must face. Some scholars have found that financial inclusion can help improve the relationship between income inequality and economic growth; that is, reducing income inequality through financial inclusion can turn the negative correlation between income inequality and economic growth into a positive correlation [73]. Several new findings have also been reported in the recent literature. In the process of poverty governance, financial inclusion and economic growth are important drivers of poverty alleviation, but the existence of income inequality will greatly reduce its poverty alleviation performance. For example, Wang et al. [74] found that economic growth played a

positive role in poverty alleviation in the BRICS countries, but rising inequality offsets the poverty alleviation effect of economic growth and weakened the effect of subsequent economic growth on poverty alleviation. Gutierrez-romero and Ahamed [30] found that in the poverty alleviation process of 121 countries around the world, the harmful impact of inequality on poverty alleviation is much greater than the positive effect of economic growth, and financial inclusion can achieve poverty alleviation by restraining the destructive impact of inequality rather than by improving economic growth. Therefore, when studying the impact of financial inclusion on poverty alleviation, scholars will also explore the impact of financial inclusion on income inequality. Some scholars believe that although inclusive finance can alleviate poverty, it cannot alleviate income inequality [14, 75]. Some studies have reached the opposite conclusion and found that financial inclusion significantly alleviates poverty rates and income inequality in developing countries [70, 76, 77]. In view of this, this article also tries to incorporate income inequality into the systematic analysis framework when examining the role of financial inclusion and economic growth in poverty alleviation in China.

In summary, the existing literature has laid the foundation for the research topic in this study, but there are still several issues that deserve further consideration. Firstly, when discussing the impact of financial inclusion on poverty alleviation, the existing literature does not strip the poverty alleviation effect of economic growth in advance, which is not conducive to identifying the real financial inclusion effect of financial inclusion. Secondly, the existing literature mainly focuses on the short-term linear relationship between financial inclusion, economic growth, and poverty alleviation, ignoring the possible endogenous problems and the long-term nonlinear relationship between variables, and these research methods need to be further explored and improved. Thirdly, there are significant differences in financial inclusion and economic development among the different regions in China. Whether there is regional heterogeneity in the impact of financial inclusion and economic growth on poverty alleviation remains to be verified. Finally, although the results of the poverty alleviation effect of financial inclusion continue to emerge, the existing literature has not given a clear answer as to whether income inequality has a negative impact on the poverty alleviation effect of financial inclusion. As a result, this study uses the panel data of 30 provinces in China from 2004 to 2019 to synthesize the financial inclusion index from the perspective of financial penetration, availability, and effectiveness. It also uses the PVAR model and time-varying nonparametric estimates technology under the theoretical framework of poverty index decomposition, so as to verify the nonlinear impact of financial inclusion, economic growth, and income inequality on poverty alleviation. This study aims at providing an indicative reference for the path selection and policy orientation of relative poverty governance.

3. Materials and Methods

3.1. Theoretical Framework. This study aims at estimating the actual impact of financial inclusion development and economic growth on poverty alleviation in China and focusing on whether there is regional heterogeneity in these impacts. Most of the studies on poverty decomposed the changes in the poverty index at different time points into the effects of economic growth and income distribution, and then discussed the effects of economic growth and income distribution on poverty alleviation [71, 78].

Based on this, we follow the poverty index decomposition theory proposed by Datt and Ravallion [71] and examine the extent to which poverty alleviation can be attributed to changes in financial inclusion and economic growth based on China's national and different regional levels. Poverty index decomposition theory is unique in that it reveals a framework for understanding poverty change, which can be decomposed into several specific components, and these components interact in complex ways. Next, referring to the research of Datt and Ravallion [71] and Luo [79], this study explains the principle of poverty index decomposition through a concise theoretical model. Given that P_t is the poverty index of a country or region in period t, according to the theoretical properties of the Lorenz curve, Datt and Ravallion [71] proved that P_t can be determined by three factors, namely, the poverty line Z_t, average income level U_t, and parameter vector $L_t(p)$ of the Lorenz curve. Then, P_t can be defined as

$$P_t = P\left(Z_t, U_t, L_t(p)\right), \tag{1}$$

$$P_t = P\left(U_t, L_t(p)\right). \tag{2}$$

Here, formula (2) is a simplified form of formula (1), indicating that there is no intertemporal change in the poverty line. Therefore, if there is no intertemporal change in the poverty line of a country or region, it can be determined that the change in the poverty index will be affected by both the average income level U_t and the change in income distribution $L_t(p)$. On this basis, assuming that period t is used as the reference period, the poverty index in period $t+n$ can be extended to the form of $P_{t+n} = P(U_{t+n}, L_{t+n}(p))$. According to Datt and Ravallion [71], the change of P_t can be subdivided into two cases. If the change in the Lorenz curve (income distribution) $L_t(p)$ is kept constant, only the average income level U_t changes; consequently, the change of poverty index P_t at this time is referred to as the growth effect. Conversely, if the change in average income level U_t is kept constant, only the Lorenz curve (income distribution) $L_t(p)$ changes; then, the change in poverty index P_t is called the distribution effect. The change in the poverty index P_t from period t to $t+n$ can be decomposed as follows:

$$\begin{aligned}\Delta P_t = &\underbrace{P\left(U_{t+n}, L_t(p)\right) - P\left(U_t, L_t(p)\right)}_{\text{growth component}} \\ &+ \underbrace{P\left(U_t, L_{t+n}(p)\right) - P\left(U_t, L_t(p)\right)}_{\text{redistribution component}} + \underbrace{\Delta R_t}_{\textit{residual}}.\end{aligned} \tag{3}$$

As shown in (3), the abovementioned poverty decomposition theory links poverty change, growth, and income distribution, providing a feasible theoretical framework for empirical analysis. Gutiérrez-Romero and Ahamed [30] believe that the theory can be implemented by regressing each component and poverty changes, and the expanded linear equation also adds financial inclusion variables. In the few available empirical studies, scholars generally use income inequality and economic growth indicators to reflect distribution and growth components, and a regression analysis using panel data usually only controls the year fixed effect. It is worth noting that the poverty decomposition theory can examine the extent to which changes in poverty at the macrolevel are attributable to the contributions of economic growth and income distribution, but it cannot capture the causal relationship between variables. In addition, in the empirical process, most of these studies use a static single equation to estimate the marginal effect coefficient of variables, which is usually plagued by endogeneity caused by reverse causality between variables. However, endogeneity has not attracted enough attention from previous scholars.

3.2. Econometric Model. According to the theoretical framework in Section 3.1, this article refers to the practices of scholars such as Abrigo and Love [80] and establishes a panel vector autoregressive (PVAR) model for empirical analysis. The PVAR model has proven to be a particularly useful tool for analyzing the dynamic interactions of endogenous variables [81], and the use of impulse response function (IRF) analysis facilitates the understanding of dynamic nonlinear connections between variables [82]. For example, when a variable is shocked by other variables, the IRF can reflect whether the response value brought by the shock is statistically significant and how it changes over time. As a simultaneous equation model, a PVAR model has the following advantages compared with a static single-equation method. Firstly, a PVAR model treats all variables in the system as endogenous variables, to effectively avoid the influence of endogenous problems on parameter estimation results. Secondly, a PVAR model can control for unobservable regional fixed effects and time fixed effects, and can also identify causal relationships between variables. Finally, through the orthogonalized impulse response function method, a PVAR model can also predict the nonlinear effects of external shocks, providing a forward-looking basis for policymaking [80]. Therefore, the PVAR model is an effective analytical tool for exploring the endogenous association of variables in the economic system. The variables are defined as poverty alleviation (RPOV), economic growth (GDP), income inequality (GINI), and financial inclusion development (IFI), these variables are called $y_{i,t}$ or $x_{i,t}$ in formula (4); I and t are used to represent different regions and years, respectively. θ_t, μ_i, and $\varepsilon_{i,t}$ are used to represent individual fixed effect, time fixed effect, and random disturbance terms, respectively. The lag order of the model was assumed to be j. The form of the PVAR model set in this article is as follows:

$$y_{i,t} = \mu_i + \theta_t + \sum_{j=1}^{n} \alpha_{i,i}^{j} y_{i,t-j} + \sum_{j=1}^{n} \beta_{i,i}^{j} x_{i,t-j} + \varepsilon_{i,t}. \tag{4}$$

The PVAR method can provide the average effect of endogenous explanatory variables on RPOV, but it cannot reveal how this average effect evolves over time before and after a certain year. For example, the financial inclusion develops vigorously after China's State Council's "Government Work Report" in 2015. Is there a significant difference before and after this critical time point? This has been a problem for a long time. One idea is to build PVAR models before and after the event and compare whether there is a significant difference in their IRFs. However, Wan et al. [83] argued that the dynamic impacts of endogenous explanatory variables given by IRF are not directly comparable, especially for the direct comparison of IRFs of two different PVAR models. In addition, we also consider that there are only 4 years of sample data after 2015, which will aggravate the sample loss in the case of subregional testing, and it seems inappropriate to use short panel data to establish the PVAR model. Therefore, we borrowed the research ideas of Hailemariam et al. [84] and continued to use nonparametric time-varying coefficient panel data models (NP-TVP) after the PVAR model to capture the time-varying effects of the main explanatory variables on RPOV. NP-TVP technology uses a pooled local linear dummy variable estimator (LLDVE), which has the advantage that it does not need to specify a certain function followed by the regime conversion in advance and allows data to directly reveal the nonlinear relationship between variables by using its own information. LLDVE was first proposed by Li et al. [85] and has been applied by Hailemariam et al. [84], Awaworyi Churchill et al. [86], and Ren et al. [87] in empirical studies. The form of the NP-TVP is as follows:

$$Y_{i,t} = f_{i,t} + \sum_{j=1}^{d} \beta_{t,j} X_{it,j} + \alpha_i + \varepsilon_{i,t}, \tag{5}$$

where $Y_{i,t}$ denotes the measure of RPOV. i and t are used to represent different regions and years, respectively. $f_{i,t}$ are unknown trend functions, and $\beta_{t,j}$ denote the time-varying coefficient estimates. α_i reflects unobserved provincial fixed effect, and $\varepsilon_{i,t}$ denotes the disturbance term. Finally, $X_{it,j}$ represents the explanatory variables of IFI, GDP, and GINI, and we are more concerned with the coefficient of IFI in empirical analysis. The confidence interval of the estimation of time-varying coefficients was also obtained by simulation with the wild bootstrap method.

3.3. Variable Definition. Economic growth variable (GDP). In empirical analyses, some studies suggest using real GDP per capita as a proxy variable for economic growth [61]. This approach is because relative to gross GDP, real GDP per capita excludes the impact of population size in different regions and can more effectively reflect the quality of economic growth [88]. However, economic growth should include the two-dimensional meaning of growth quality and growth rate. Real GDP per capita reflects the quality

dimension of economic growth, while the real GDP growth rate can reflect the speed dimension. Under the framework of poverty index decomposition theory, this study prefers to interpret economic growth from the perspective of speed. Therefore, following the practice of scholars such as Erlando et al. [10] and Gutiérrez-Romero and Ahamed [30], the real GDP growth rate is used here to measure the economic growth level of each province in China.

Income inequality variable (GINI). The existing literature has basically reached a consensus on the measurement of income inequality, and the Gini coefficient is used as a general indicator to measure income inequality. The Gini coefficient has the advantages of comparability in both time and space, and its value range is between 0 and 1. The larger the value, the higher the inequality of income distribution. However, in the past, scholars have mostly used national-level household income sample survey data to measure the Gini coefficient. The results obtained in this case can only reflect income inequality at a national level and rarely provide detailed results of the Gini coefficient of each province in China. Therefore, this article uses the research ideas of Tian [89] to measure the Gini coefficient of each province by using household income group data at the macrolevel. The specific calculation formula is as follows:

$$\mathrm{GINI}' = 1 - \frac{1}{PW}\sum_{j=1}^{n}\left(W_{i-1} - W_i\right) \times P_i, \tag{6}$$

$$\mathrm{GINI} = P_c^2\frac{u_c}{u}G_c + P_r^2\frac{u_r}{u}G_r + P_cP_r\frac{u_c - u_r}{u}. \tag{7}$$

Formula (6) is an improved Gini coefficient expression based on the Lorenz curve principle. Among them, P is the total population, W is the total income, W_i is the income accumulated by the i-th group, and P_i is the proportion of the i-th group's population compared to the total population. On this basis, the Gini coefficients of urban residents and rural residents in each province can be calculated by using income grouping data; then, the overall Gini coefficient can be calculated by using the "group weighting method" shown in formula (7). In formula (7), G_c and G_r represent the Gini coefficient of urban and rural residents, respectively; P_c and P_r represent the proportion of urban and rural populations, respectively; u_c and u_r represent the per capita income of urban and rural residents, respectively; and u represents the per capita income of the province in which residents live.

Poverty alleviation variable (RPOV). Indicators of poverty alleviation are diverse, and the proxy variables used by scholars are also quite different. Most studies use poverty incidence as a proxy variable for poverty alleviation [10, 30]. However, there are two difficulties in using poverty incidence indicators. First, it involves setting the poverty line standard. The common practice is to refer to the poverty line standard provided by the World Bank, but this standard has the problem of being too absolute. Second, domestic statistical data are relatively scarce, and it is difficult to collect long-term dynamic poverty incidence data for each province. Therefore, referring to Li and Han [20], this article uses the proportion of the minimum living security population in the total regional population to reflect the incidence of poverty at the provincial level. The minimum living security population refers to the sum of the minimum living security population of urban residents and rural residents.

Financial inclusion development variable (IFI). Given that financial inclusion is a multidimensional concept, previous studies have generally adopted the method of constructing a comprehensive index to measure the development of financial inclusion [13]. Among them, the index system designed by Sarma [90], Allen et al. [91], and Park and Mercado [14] are highly influential. They measure the comprehensive index of financial inclusion primarily from three dimensions of permeability, availability, and effectiveness. However, Pesqué-Cela et al. [92] systematically reviewed this and concluded that there is no universal financial inclusion indicator system, and indicators should be flexibly adjusted according to the actual conditions of different countries. Based on this, this study inherits the research ideas of the abovementioned literature and constructs an indicator system for the development of financial inclusion in China from four dimensions: geographic penetration, population penetration, service availability, and effective use. Specifically, the ratio of regional banking financial institutions to geographic area and the ratio of employees of banking financial institutions to geographic area are used to reflect the geographic penetration dimension. The dimension of population penetration is characterized by the ratio of regional banking financial institutions to the regional population and the ratio of employees in banking financial institutions to the regional population. The dimension of service availability is reflected by the ratio of the loan balance of regional financial institutions to the regional GDP and the balance of deposits of regional financial institutions to the regional GDP. The dimension of effective use is measured by indicators of the per capita loan balance of regional financial institutions and the per capita deposit balance of financial institutions. Finally, the specific formula for calculating the financial inclusion index in this study is as follows:

$$\mathrm{IFI} = 1 - \frac{\sqrt{\left(w_{1,t} - s_{1,t}\right)^2 + \left(w_{2,t} - s_{2,t}\right)^2 + \ldots + \left(w_{m,t} - s_{m,t}\right)^2}}{\sqrt{\left(w_{1,t}\right)^2 + \left(w_{2,t}\right)^2 + \ldots + \left(w_{m,t}\right)^2}}. \tag{8}$$

Formula (8) is the expression of the synthetic comprehensive index. Among them, IFI represents the comprehensive index of financial inclusion development, $w_{m,t}$ is the weight of the m-th indicator calculated according to the coefficient of variation method in period t, and the coefficient of variation can be calculated by the ratio of the standard deviation to the mean of the m-th indicator in each province in period t. $s_{m,t}$ represents the weighted value of the m-th indicator in each province in period t, and each indicator needs to be dimensionless and processed by the range standardization method in advance.

3.4. Data Sources. Based on the principles of data availability, continuity, and comparability, this study utilizes the balanced panel data of 30 provinces in China from 2004 to

2019 for empirical analysis (excluding Tibet, Taiwan, Hong Kong, and Macau for reasons of data availability). Furthermore, according to the division method of China's "Seventh Five-Year Plan (1986–1990)," the country is divided into three types of economic regions: eastern, central, and western. The eastern region includes 11 provinces (or cities) including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes 9 provinces (or autonomous regions) including Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. The western region includes 10 provinces (or autonomous regions) including Sichuan, Chongqing, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. It should be emphasized that the Chinese government has set up Liaoning, Jilin, and Heilongjiang as the Northeast Economic Zone separately in the "Eleventh Five-Year Plan (2006–2010)," and this division method of east, middle, west, and northeast is still in use today. However, considering the small sample size of the Northeast Economic Zone, many scholars still tend to use the traditional three major economic zones for empirical analysis. For recent related literature, please refer to Shi and Xu [93], Fan et al. [94], Ke et al. [95], Liu et al. [96], Ren et al. [97], and Luo et al. [98]. The economic growth rate, loan balance of financial institutions, deposit balance of financial institutions, and GDP data of each region are sourced from the official website of the National Bureau of Statistics of China. The income group data of urban and rural residents and the regional population data are from the "China Statistical Yearbook" and the "Statistical Yearbook" of various regions spanning several years. The minimum subsistence allowance population data are sourced from the "China Civil Affairs Statistical Yearbook" spanning several years and supplemented by the "China Statistical Yearbook." In addition, the number of banking financial institutions and the number of employees of banking financial institutions are sourced from the provincial "Regional Financial Operation Report" issued by the People's Bank of China. Finally, individual missing values were supplemented by querying the Statistical Yearbook of each region. The empirical aspect of this study was processed by Stata 17.0 software. Table 1 lists the descriptive statistics of all the variables.

Table 1: Descriptive statistics of variables.

Variable	Obs	Mean	Std.	Dev.	Min	Max
GDP	480	0.101	0.029	0.005	0.005	0.196
RPOV	480	0.049	0.034	0.002	0.002	0.169
GINI	480	0.476	0.058	0.316	0.316	0.656
IFI	480	0.439	0.281	0.013	0.013	0.997

4. Results and Discussion

4.1. Unit Root Test. Classical econometric theory holds that, before performing panel data regression analysis, a unit root test must be performed on variables to avoid the pseudoregression problem that may be caused by nonstationary variables. In addition, as pointed out by Blundell and Bond, when the variables have unit roots in a regression analysis, the generalized method of moments (GMM) will face the problem of weak instrumental variables [99]. Therefore, the stationarity of endogenous variables is a prerequisite for establishing a PVAR model. The null hypothesis of the panel unit root test is that the variable has a unit root; that is, the variable is a nonstationary panel sequence. If the result of the unit root test rejects the null hypothesis, it can be considered that the variable meets the requirements of stationarity. In order to obtain a robust panel unit root test conclusion, this study adopts both the homogeneity LLC test and the heterogeneity IPS test. The specific test results are shown in Table 2. It can be seen from Table 2 that although the RPOV variable in the western region is not significant in the IPS test, the LLC test results are highly significant at the 1% level, and the rest of the variables have passed the significance test at the 10% level. Therefore, it can be considered that each variable is a stationary panel series. In fact, many literature studies often provide the results of panel cointegration tests after unit root tests, and panel cointegration tests are not a critical step when we use stationary variables to build PVAR models. However, in the case that the original data have a unit root, the panel cointegration test can help us further confirm whether there is a long-term stable equilibrium relationship between these variables, which is an important basis for continuing to build a PVAR model [100, 101].

4.2. Model Estimation and Stability Test. The following details must be considered when using a PVAR model. It is necessary to select an appropriate model lag order, the overidentification test of instrumental variables cannot be ignored, and the PVAR model must be stable. Abrigo and Love [80] pointed out that the parameters and moment conditions of the PVAR model depend on the selection of the optimal lag order, and the choice of different lag orders may affect the estimation results of the model. A common practice is to use MAIC, MBIC, and MQIC statistics as the judgment criteria, and the minimum value among the three can be selected as the optimal lag order. However, this approach also requires the maximum lag period of the PVAR model to be specified in advance, so researchers must seek a compromise between the optimal lag period and model stability. Therefore, this study first sets the maximum lag as 4 based on the number of sample periods. Then, MAIC, MBIC, and MQIC statistics were comprehensively compared; the optimal lag order of the national sample PVAR model was set as order 2 and the optimal lag order of the eastern, central, and western PVAR model was set as order 1. In addition, when estimating the PVAR model it is also necessary to pay attention to the control of time and regional fixed effects. If the model is affected by potential factors that do not change with time or region, the PVAR estimation results will be biased and inconsistent. In this article, the generalized method of moments (GMM) method was used to obtain a consistent estimator, the time fixed effect was removed by the within-group mean difference method in advance, and the Helmert transformation method was then used to remove the regional fixed effect. These

Table 2: Unit root test of variables.

Variable	National		Eastern		Central		Western	
	LLC test	IPS test	LLC test	IPS test	LLC test	IPS test	LLC test	IPS test
GDP	−5.867*** (0.000)	−5.464*** (0.000)	−2.910*** (0.002)	−5.516*** (0.000)	−3.588*** (0.000)	−3.454*** (0.000)	−3.865*** (0.000)	−6.657*** (0.000)
RPOV	−5.562*** (0.000)	−6.656*** (0.000)	−4.445*** (0.000)	−3.119*** (0.001)	−1.442* (0.075)	−2.626*** (0.004)	−3.933*** (0.000)	−0.386 (0.350)
GINI	−7.578*** (0.000)	−4.808*** (0.000)	−2.658*** (0.004)	−4.129*** (0.000)	−4.129*** (0.000)	−1.717** (0.043)	−6.379*** (0.000)	−3.509*** (0.000)
IFI	−2.259** (0.012)	−2.774*** (0.003)	−2.626*** (0.004)	−5.176*** (0.000)	−1.969** (0.025)	−1.955** (0.025)	−2.633*** (0.004)	−2.830*** (0.002)

The values in the table correspond to the adjusted t-statistic of the LLC test and the Wt-bar statistic of the IPS test. The corresponding significance probability p values are in parentheses; ***, **, and *represent significance at the 10%, 5%, and 1% levels, respectively.

Table 3: GMM estimation results of the PVAR model.

RPOV	National	Eastern	Central	Western
L.GDP	0.028 (0.623)	−0.050*** (0.000)	−0.049* (0.069)	−0.060 (0.527)
L2.GDP	−0.062 (0.219)			
L.RPOV	0.886*** (0.000)	0.422*** (0.000)	0.714*** (0.000)	1.020*** (0.000)
L2.RPOV	0.106 (0.396)			
L.GINI	0.128** (0.040)	−0.046*** (0.006)	−0.092*** (0.000)	0.162* (0.054)
L2.GINI	−0.043 (0.282)			
L.IFI	−0.031** (0.012)	−0.010*** (0.000)	−0.010*** (0.001)	−0.058*** (0.000)
L2.IFI	−0.002 (0.830)			
Time fixed effects	Yes	Yes	Yes	Yes
Provincial fixed effects	Yes	Yes	Yes	Yes
Hansen's J	18.707 (0.284)	39.853 (0.160)	82.806 (0.393)	30.723 (0.531)
Observations	390	154	126	140

L represents the variable first-order lag. The significance probability p value is in parentheses; ***, **, and *represent significance at the 10%, 5%, and 1% levels, respectively. Due to space limitations, only the regression results of the RPOV variable are reported in the table.

practices minimize sample size loss, and lagged variables can still be used as valid instrumental variables for GMM estimation.

Table 3 reports the parameter estimation results of RPOV for each variable in the PVAR model. Hansen's J test shows that all instrumental variables are valid, and the reasonableness of the model estimation results is satisfied. From the estimated results, there is obvious regional heterogeneity in the impact of GDP on RPOV. The lagged value of GDP in the eastern region and central region has a significant negative impact on RPOV, although it is not significant in the western regions. The development of IFI has a significant role in promoting RPOV, which initially means that the development of IFI can be an important path for RPOV in China. In the regression of GINI on RPOV, its coefficients have different degrees of influence in different regions, which preliminarily suggests that the impact mechanism of income inequality on poverty alleviation is different. Finally, the lag term of RPOV has a consistent impact on itself and its coefficients are significantly positive at the 1% level, which means that RPOV has a strong sticky effect. If the trend of RPOV cannot be effectively controlled, the regional poverty level will only worsen on the current basis. In the following sections, we will combine the impulse response function and the variance decomposition results to analyze the nonlinear effect between variables.

Figure 1 shows the stability test results of the PVAR model. The PVAR model can judge the stability of the estimation results by fitting the reciprocal of the eigenvalue modulus in the model. If the reciprocal of the eigenvalue modulus of the adjoint matrix in the PVAR model is within the unit circle, it means that the constructed model satisfies the stability condition [80, 102]. As shown in Figure 1, within the four groups of PVAR models in the national, eastern, central, and western regions, the reciprocal of each eigenvalue modulus is located inside the unit circle, and the reciprocal of each eigenvalue modulus is strictly less than 1. Therefore, the PVAR model established in this study satisfies the stability condition.

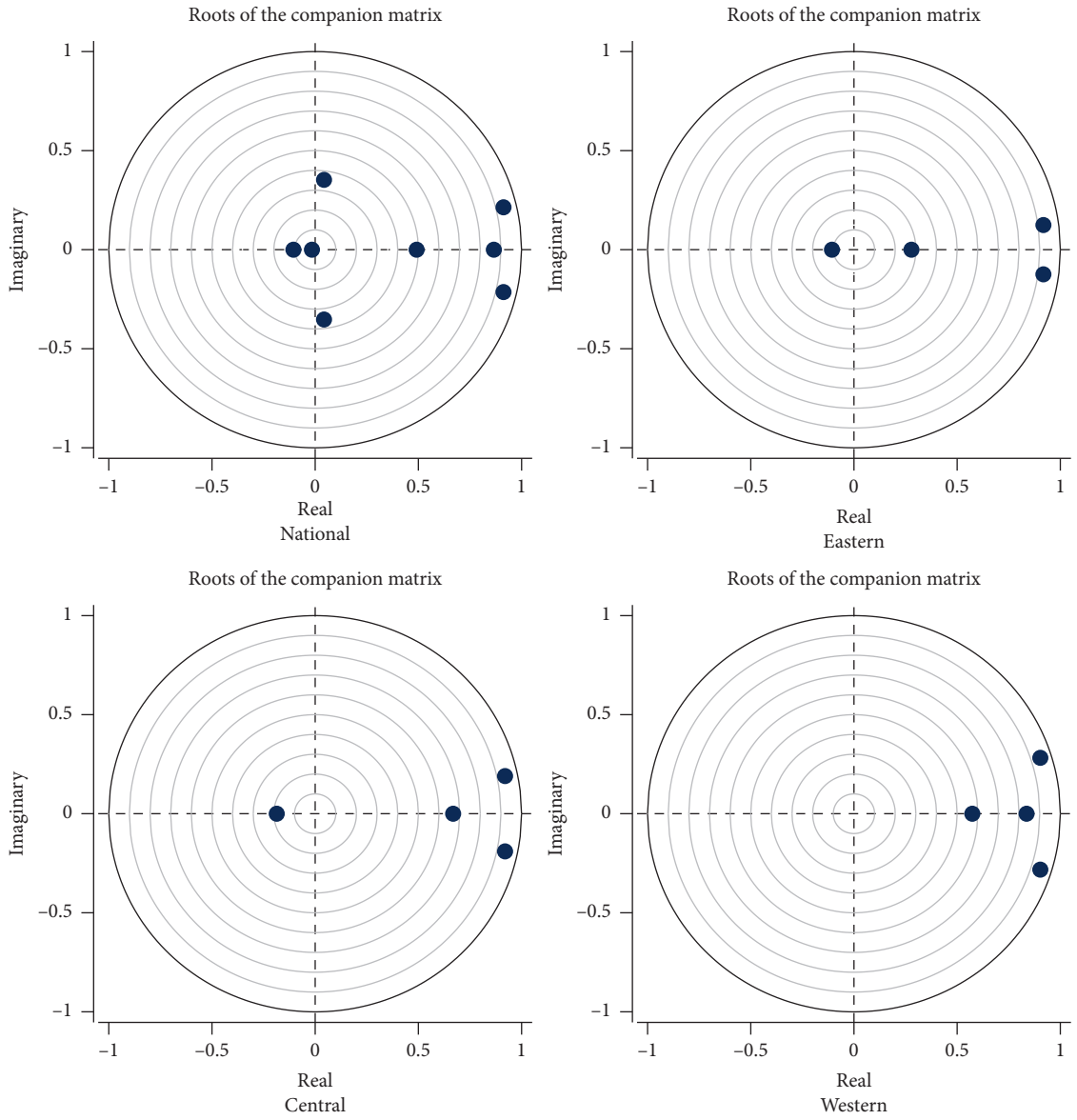

Figure 1: Stability test of the PVAR model.

4.3. Granger Causality Test. Like the time series VAR model, the PVAR model can also verify whether there is a causal relationship between economic variables. Table 4 reports the results of the panel Granger causality test to confirm the direction of the causal effect of each explanatory variable on RPOV. The Granger causality test is essential to test whether the lagged value of one variable can be introduced into the equation of other variables, and to judge whether the addition of lagged variables can improve the overall explanatory power of the equation, the panel Granger causality Wald test must be carried out under the framework of the existing PVAR model [103]. We make the null hypothesis that there is no causal relationship from the independent variable to the dependent variable, and the alternative hypothesis is that the independent variable is the Granger cause of the dependent variable, which can be judged by the p value of the corresponding statistic. As shown in Table 4, there is a two-way Granger causality between GDP and RPOV in the eastern and central regions, and the null hypothesis is rejected at the 1% significance level. However, for the national and western regions, GDP is the only Granger cause of RPOV, and the null hypothesis is significant at the 1% and 5% levels, respectively. Similarly, there is a two-way Granger causality between GINI and RPOV in the eastern and central regions at the 5% levels. However, there is only a one-way Granger causality from RPOV to GINI across the national and western regions at the 5% levels. In addition, there is only a two-way Granger causality between GDP and GINI in the national and central regions at the 1% level, and only one-way Granger causality from GINI to GDP in the eastern and western regions. In particular, the empirical results demonstrated that there is strong support at the 1% level that IFI is the Granger cause of GDP, but the assumption that GDP is the Granger cause of IFI does not hold

Table 4: Panel granger causality test.

Null hypothesis	Chi^2 statistic			
	National	Eastern	Central	Western
GDP is not a granger reason for RPOV	19.543*** (0.000)	139.530*** (0.000)	11.480*** (0.001)	5.078** (0.024)
GDP is not a granger reason for GINI	16.575*** (0.000)	1.311 (0.252)	24.541*** (0.000)	0.000 (0.982)
GDP is not the granger reason for IFI	3.859 (0.145)	29.326*** (0.000)	17.135*** (0.000)	3.581* (0.058)
RPOV is not a granger reason for GDP	2.072 (0.355)	22.396*** (0.000)	3.295*** (0.069)	0.400 (0.527)
RPOV is not a granger reason for GINI	4.788* (0.091)	7.412*** (0.006)	36.849*** (0.000)	3.72* (0.054)
RPOV is not a granger reason for IFI	8.757** (0.013)	13.038*** (0.000)	11.849*** (0.001)	12.884*** (0.000)
GINI is not a granger reason for GDP	23.418*** (0.000)	101.424*** (0.000)	208.324*** (0.000)	3.427* (0.064)
GINI is not a granger reason for RPOV	0.706 (0.702)	89.795*** (0.000)	7.827*** (0.005)	0.033 (0.855)
GINI is not a granger reason for IFI	6.300** (0.043)	0.892 (0.345)	1.241 (0.265)	8.298*** (0.004)
IFI is not a granger reason for GDP	27.021*** (0.000)	149.635*** (0.000)	75.887*** (0.000)	8.870*** (0.003)
IFI is not a granger reason for RPOV	41.158*** (0.000)	143.092*** (0.000)	106.827*** (0.000)	47.599*** (0.000)
IFI is not a granger reason for GINI	1.628 (0.443)	2.640 (0.104)	1.013 (0.314)	3.718* (0.054)

The significance probability p value is in parentheses; ***, **, and *represent significance at the 10%, 5%, and 1% levels, respectively.

at the national level. Finally, there is a two-way Granger causality between IFI and RPOV in the national, eastern, central, and western results, and the null hypothesis is rejected at least at the 1% significance level. The above results show that there is mutual influence among the four endogenous explanatory variables, and the conclusion further supports the necessity of using the PVAR model in this article. From the perspective of policy implications, the path of GDP, IFI, and GINI can effectively affect RPOV. However, given the complex causal relationship among various variables, government departments must take regional heterogeneity into account when formulating poverty alleviation strategies.

4.4. Analysis of Impulse Response Function. In order to further investigate the interactive relationship between GDP, GINI, IFI, and RPOV, we utilize the impulse response function (IRF) to analyze the shock effects among variables. More precisely, IRF reflects the dynamic impact of the shock variable on the response variable in different time horizons; that is, when the error term in each model is subjected to an external shock of one standard deviation, how the response variable changes over time in the present and future [83]. Since the construction of the IRF matrix in the PVAR model depends on regression parameters, a Monte Carlo simulation and bootstrap sampling methods can be used to estimate the confidence interval of the IRF [80]. Therefore, if the 0 horizontal line lies outside the confidence interval, we consider the IRF to be statistically significant [102]. We calculated the standard error of the IRF using the Monte Carlo simulation (1000 times) method and then obtained the confidence interval with a confidence level of 95%. The confidence interval gives the 2.5% and 97.5% quantile values of the IRF, and some studies have expanded the confidence interval to the 90% confidence level for analysis as needed [104]. Figures 2–5 show the orthogonalized IRFs in different regions. The solid and dotted lines in the figures represent the IRF and its confidence interval curve, respectively. The horizontal and vertical axes represent the prediction time and IRF value, respectively. An important feature of IRF is that it tends to be stable in the long run, which means that the IRF can indicate the time it takes for the sequence to converge to a steady state after a shock [105]. In this article, the prediction time is set to 20 to observe whether there is a convergence trend of IRF. In fact, many of the IRFs in Figures 2–5 were no longer significant after 15 periods. In the end, we found that extending the prediction time (30 or 40) gave the exact same conclusion, and all IRFs converged to 0 in the long run, which means that the convergence rate of IRFs is relatively slow. The reason may be that, as pointed out by Enders [106] in the book, the stability of the system determines the convergence, and if the reciprocal of each eigenvalue modulus is gathered at the centre of the circle (see Figure 1), the convergence rate of the IRF may be accelerated.

Figure 2 shows the results of the IRF analysis of the national sample. As can be seen, the impulse response of GINI to a standard deviation shock from IFI is positive and statistically significant, but this positive effect is only significant in the four periods after the shock, and over time, this positive effect is no longer significant and gradually converges to 0. The impact of IFI has a significant negative effect on RPOV. The value of IRF increases rapidly with time and reaches a maximum value (−0.005) in the 5th period, after which this effect gradually decays and is no longer significant, and the IRF shows an obvious positive U-shape from the 1st to the 10th period. However, the response of GDP to IFI shocks is always not significant. In addition, the shock response of each variable to GINI is relatively weak, except that the short-term shock of GINI to itself has a positive response in the first two periods, and the rest of the variables showed a significant shock response in the current period, but the absolute values of these IRFs are almost all close to 0. Furthermore, the response value of IFI increased rapidly under a one-unit RPOV shock and reached a maximum value (0.117) in the 7th period, and then, this positive effect gradually decayed and became insignificant after the 10th period. Similarly, the positive effect of RPOV shock on GINI also showed a characteristic of increasing first and then decreasing with time. In other words, we found that the effects of RPOV on both IFI and GINI exhibited a

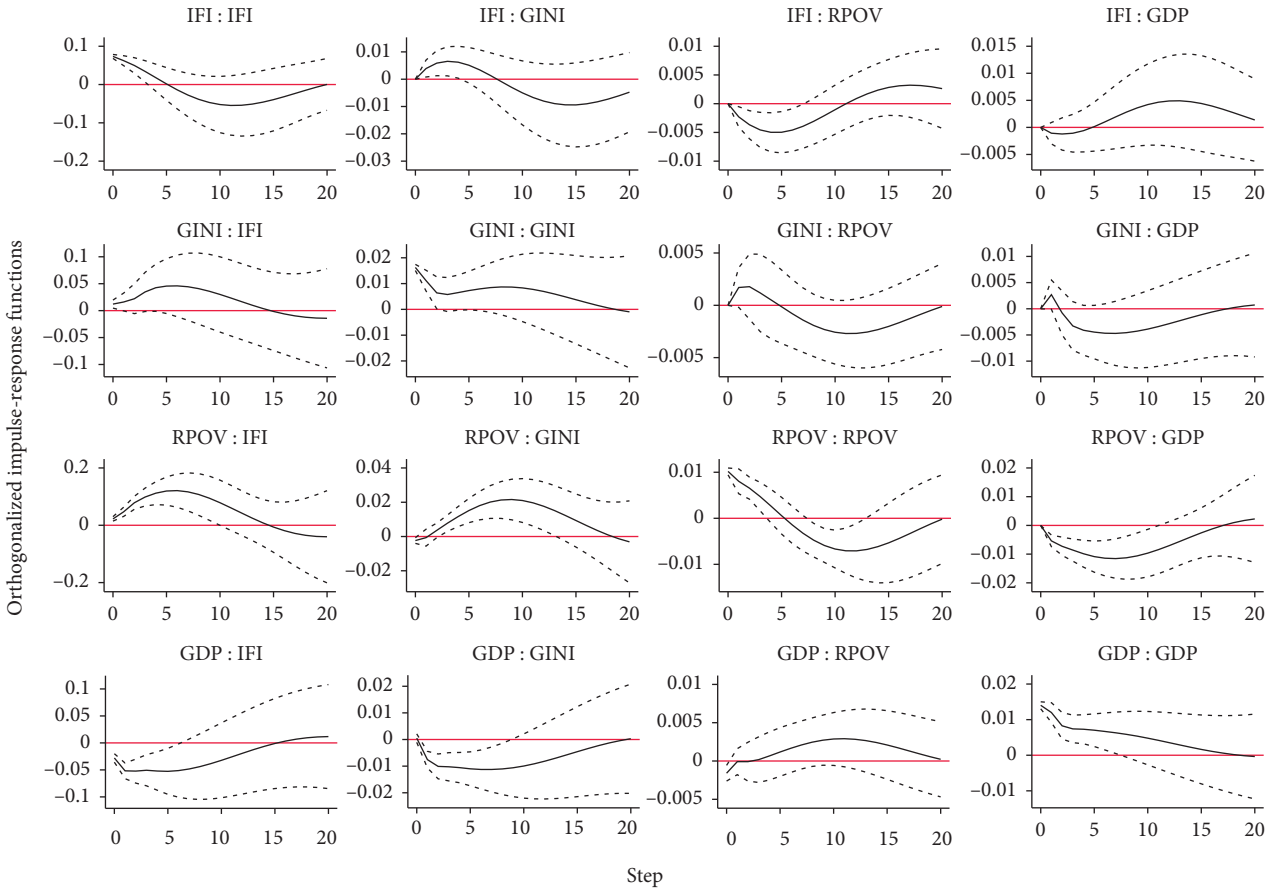

Figure 2: Impulse response function at the national level.

very distinct inverted U-shaped feature. The negative response of GDP to the RPOV shock showed a positive U-shaped characteristic, and the value of the IRF gradually increased with time and reached a maximum value (−0.012) in the 7th period, and then, this effect gradually decayed and was no longer significant by the 12th IRF. Finally, IFI and GINI have a significant negative response to GDP shock, and the IRF values of the 5th period (−0.053) and the 7th period (−0.011) reached the maximum value, but the IRF of economic growth on poverty alleviation was only significant in the 1st period, which means that the impact of economic growth on RPOV is short term. In general, at the national level, the interaction of all variables is nonlinear, and the IRFs all show obvious positive U-shaped or inverted U-shaped characteristics.

The above results show that although the development of financial inclusion at the macrolevel increases income inequality in the short term, it can effectively promote poverty alleviation in the long term. This is consistent with the results of Gutiérrez-Romero and Ahamed [30], who argue that this effect is a combined result of the indirect effect of inequality on poverty alleviation and the direct effect of financial inclusion development on poverty alleviation. Compared with the conclusion of Erlando et al. [10], we found no evidence that economic growth will lead to poverty in the initial stage of the shock, and the results show that economic growth has a significant inhibitory effect on poverty in the early stage. Scholars believe that economic growth can greatly promote poverty alleviation, and the increase in income inequality may offset part of the poverty alleviation effect of economic growth [79]. However, our empirical results show that economic growth has played a positive role in alleviating poverty and reducing income inequality, and poverty alleviation in turn reduces income inequality and promotes economic growth. Income inequality only offsets part of the poverty alleviation effect of financial inclusion development. On the one hand, it is evident that the development of financial inclusion has indeed expanded opportunities for the disadvantaged in China to obtain financial services, enhanced the economic capacity of the disadvantaged, and improved the level of welfare; economic growth also plays a key role in the process of poverty alleviation. On the other hand, the policy goal of financial inclusion is to make financial services more accessible to the disadvantaged, but given the differences in the ability of the rich and the poor to access credit funds, if the rich benefit more from it, it will lead to increased income inequality [107], thereby weakening the poverty alleviation effect of financial inclusion. Therefore, policy departments should not only pay attention to the impediment of unbalanced income distribution to poverty alleviation, but also further improve the targeted benefit of poor groups during the implementation of financial inclusion policies, so that financial resources can more accurately reach target groups.

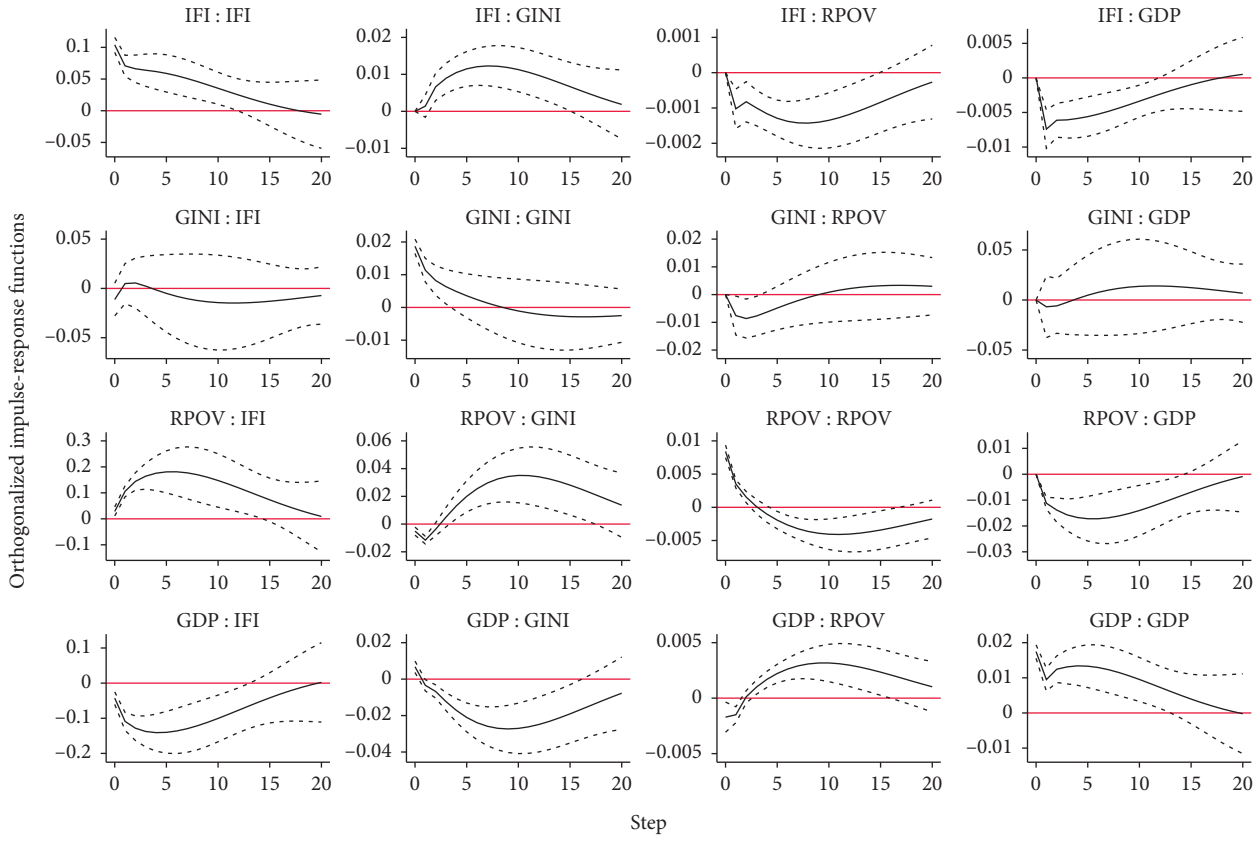

Figure 3: Impulse response function in the eastern region.

Figure 3 presents the results of the IRF analysis for the eastern region. When faced with the shock of one standard deviation of IFI, RPOV and GDP show a negative response, while GINI shows a positive response to the shock. Specifically, the shock response of GINI became significant in the second period, and the response intensity reaches the maximum value (0.012) in the 8th period, and the IRF converges to 0 after gradually decaying. The shock response of RPOV showed a fluctuating increase with time and decreased rapidly after reaching the maximum value (−0.002) in the 8th period, and the IRF basically tended to a steady state after the 15th period. Therefore, their IRFs resemble inverted U-shaped or positive U-shaped curves, respectively. The shock response of GDP is a positive V-shape, and the response remains significantly negative, with the maximum value of IRF (−0.006) occurring in the 2nd period. The response of each variable to GINI shock is relatively weak, and only RPOV has a significant short-term negative response to GINI shock. Similar to the empirical results from a national perspective, the RPOV shock has a significant positive impact on IFI, the IRF reaches a maximum value (0.181) in the 6th period, and then, the IRF tends to 0 after gradually weakening in the 5th to 15th period. The response of GINI to RPOV shocks remained negative in periods 1-2, but shifted to a positive effect that first enhanced and then weakened in periods 3–15, and its maximum value (0.035) occurred in period 10. This means that the responses of IFI and GINI to poverty shocks are both inverted U-shaped relationships. On the contrary, GDP has a significant negative response to RPOV shock, with a maximum value (−0.017) occurring in the 6th period, and its IRF exhibits a positive U-shape and returns to steady state in the long run. In addition, GDP shock has a significant negative effect on IFI, with IRF showing a positive U-shape and reaching a maximum (−0.141) in the 4th period. The impact of GDP on GINI is positive at the beginning of the shock and turns negative at the beginning of the second period, its IRF reaches the maximum value (−0.027) in the 9th period, and the IRF also shows a positive U-shape. The impact of GDP on RPOV was negative in periods 1-2 and positive in periods 2–15, and the maximum value of IRF (0.003) occurred in period 10. Therefore, given that the IRF in the eastern region is mainly U-shaped or inverted U-shaped, we believe that there is a significant dynamic nonlinear relationship between the variables.

The above results show that the development of financial inclusion is effective in promoting poverty alleviation in the eastern region, but it also has a negative impact on income inequality, which further supports the views of Gutiérrez-Romero and Ahamed [30]. The existing literature generally suggests that financial inclusion can improve income inequality [108], but we believe that the development of financial inclusion exacerbated income inequality in eastern China. This result also verifies the previous research conclusions of Huang and Zhang [57] that the development of financial inclusion has amplified income inequality in China

in the short term. In addition, economic growth in the eastern region inhibits the development of financial inclusion and promotes long-term poverty, indicating that financial inclusion and economic growth are not coordinated to play a role in poverty alleviation, which is contrary to the conclusions of Qian et al. [60]. One of the reasons is that China's economic reform has spatially nonequilibrium characteristics, prioritizing the development of the eastern region's economic level and financial inclusion and lowering the threshold for the transfer of labor from traditional sectors to modern industrial sectors; income inequality will widen as the share of modern industrial sectors rise [109]. Secondly, China's financial inclusion system is still dominated by state-owned institutions, but it is difficult for the target group served by state-owned banks to move down to the poor. Information asymmetry may lead to the phenomenon of "financial exclusion" in a financial inclusion policy, leading to the group with capital needs being unable to benefit from financial services [20, 59]. Some scholars believe that financial exclusion will not only widen the income gap [11], but even have a depressing effect on economic growth [59]. Therefore, while maintaining rapid economic growth, the eastern region should establish a diversified supply channel of financial inclusion to reduce the negative impact of financial exclusion, which is crucial to promoting regional poverty alleviation and economic growth.

Figure 4 shows the results of the IRF analysis for the central region. As can be seen, GINI does not show a significant response when shocked by one standard deviation of IFI, but RPOV has a significant negative response to this shock. After being shocked by one unit of IFI, the RPOV will have a gradually increasing negative response, and the IRF will reach the maximum value (−0.002) in the 7th period, and then, the effect will gradually weaken and converge to 0 in the long run. Similarly, the response trend of GDP to IFI shock is basically consistent with that of RPOV, and their IRF shows a U-shaped curve. However, for the shock of one standard deviation of GINI, IFI only produced significant positive responses in the first two periods; then IRF converged rapidly. On the contrary, GDP rapidly produced a negative response and the response amplitude continued to expand, reached the maximum value (−0.005) in the first period, and then gradually weakened; IRF showed a V-shaped curve. Interestingly, although the response of GINI to its own shock was always positive during period 1–10, IRF showed a decreasing trend from strong to weak, which means that GINI has a long-term inertia effect. The RPOV shock in the central region still has a significant positive impact on IFI, the maximum response amplitude (0.056) appeared in the 5th period, the IRF gradually increased before the 5th period, and the IRF gradually weakened after the 5th period, until the effects begin to disappear after the 13th period. In addition, the RPOV shock had a significant positive impact on GINI and had a significant negative impact on GDP, and the IRF presented a positive U-shape and an inverted U-shape, respectively, indicating that the response amplitudes increased first and then decreased with time, and the maximum values appeared in period 8 (0.006) and period 6 (-0.005), respectively. The response of RPOV to its own shock is U-shaped. Before the 5th period, it mainly has a positive effect, but after the 5th period, it mainly has a negative effect. The IRF gradually converges to 0 after the 17th period, indicating that poverty also has a strong inertial effect. Finally, when shocked by one standard deviation of GDP, the IFI and GINI have a significant short-term negative response to the shock, and their IRFs both exhibit the characteristics of a V-shaped curve with their respective maximum values (−0.051 and −0.014) both appearing in the first period. Although GDP shocks have a significant positive effect on RPOV, the IRF immediately generates a significant positive response and declines sharply in the first period. After the second period, the IRF begins to show an inverted U-shaped relationship, which gradually converges to 0 after reaching the maximum value in the sixth period. Overall, the empirical results in the central region are basically consistent with those in other regions.

The above empirical results still support the theoretical mechanism that financial inclusion development helps poverty alleviation, which is consistent with the direction of influence in the national and eastern regions. Research shows that there are obvious differences in the level of financial inclusion and poverty among different regions in China [5], and there is a significant negative relationship between the level of financial inclusion and poverty in the eastern and central regions [110]. However, the dynamic relationship between financial inclusion development and poverty alleviation in the central region shows a long-term impact, which is no different from the mid- and long-term impacts in the national and eastern regions. A possible reason is because the Rise of Central China Plan started in 2004 and has transferred a large amount of funds to the central region to support economic development, which has improved the level of financial inclusion in the central region [13]. Income inequality and poverty levels in the central region are at moderate levels in all regions, and the relative balance between financial inclusion and economic development makes the short-term poverty alleviation effect of financial inclusion more obvious. The effect of financial inclusion on income inequality in the central region is not significant, which is consistent with the findings of Park and Mercado [14], who point out that it is questionable whether financial inclusion in developing Asian countries (especially China) has any inhibitory effect on income inequality. Furthermore, economic growth in the central region helps reduce income inequality, a finding which supports the main conclusions of Hailemariam et al. [84], who examined the determinants of income inequality and argued that economic growth leads to a significant reduction in income inequality. Overall, the improvement of income inequality in the central region primarily depends on the path of economic growth, while financial inclusion mainly plays a role in poverty alleviation. In the future, government departments should pay attention to the breadth and depth of financial inclusion development, and actively guide the flow of funds among different income groups, so that financial inclusion can also form a supporting role in reducing income gaps.

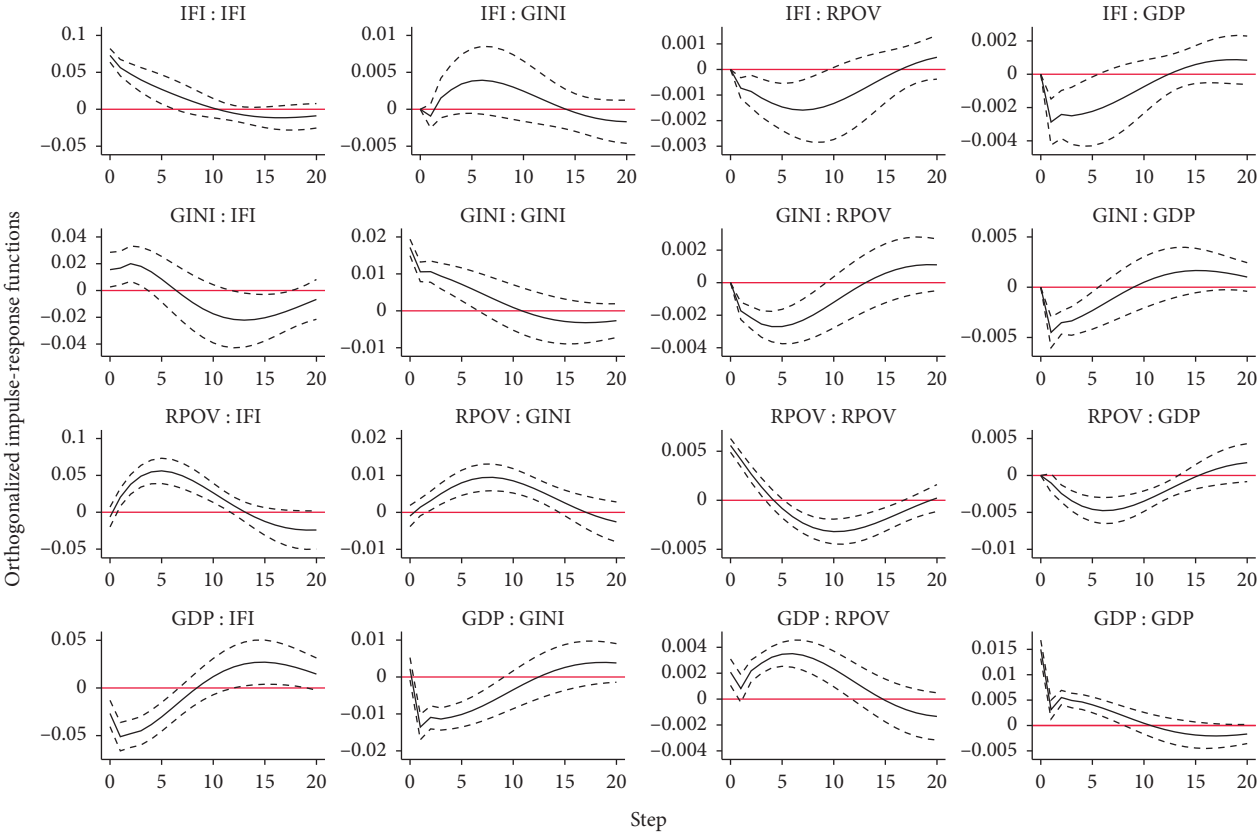

Figure 4: Impulse response function in the central region.

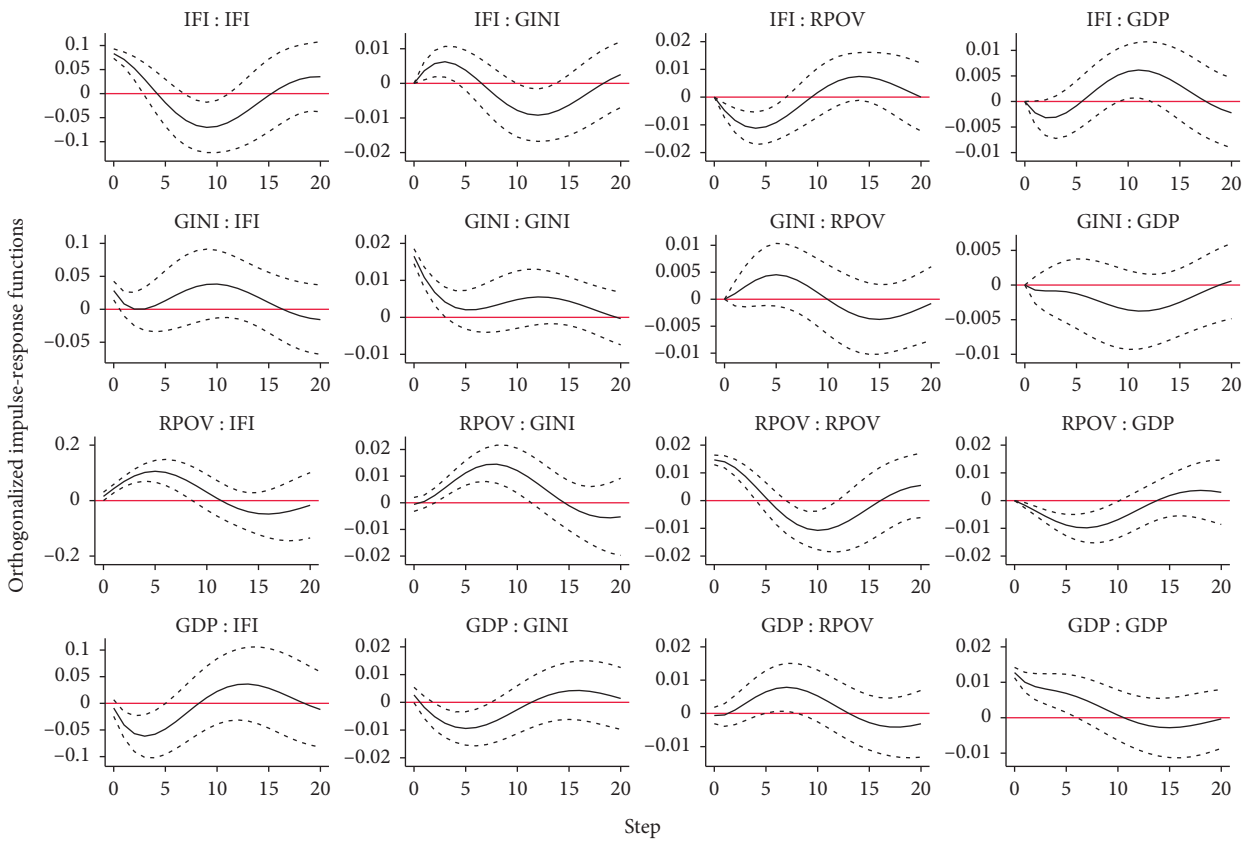

Figure 5: Impulse response function in the Western region.

Figure 5 shows the IRF of various variables in the western region to external shocks. RPOV still has a significant negative response to the IFI shock. Specifically, the impact of IFI on RPOV has a positive U-shape, reaching a maximum (−0.011) in the 4th period after the shock and then gradually weakening the response range. IFI has a significant positive effect on GINI, and the impulse response curve exhibits an inverted U-shaped short-term characteristic, which is highly consistent with results across the national, eastern, and central regions. Similar to the results in the national and eastern region, we found no evidence that the GINI shock led to changes in GDP and RPOV, which only had a transient-positive effect on themselves. After being shocked by one standard deviation of RPOV, in addition to a certain inertial impact on itself, IFI shows a significant positive response, the IRF reaches a maximum value (0.106) in the 5th period, and then, the response amplitude gradually decays, and the effect disappears after the 9th period. Therefore, the effect of RPOV on IFI and GINI is also inverted U-shaped, which is completely consistent with the empirical results in other regions. Another result is that the influence of RPOV on GDP shows a positive U-shaped curve, but it always remains negative in period 1–14, and the maximum value (−0.010) appears in period 8; this conclusion is also very robust. Finally, for IFI and GINI, when they were impacted by one standard deviation of GDP, they both immediately had a significant negative impact in the 1st period. The maximum value of the IFI response (−0.062) appeared in the 3th period, while the maximum value of the GINI response (−0.009) appeared in the 5th period; IRFs all show a positive U-shaped relationship. However, their IRFs were insignificant in periods 6 and 7, respectively, implying that the impact on GDP was short-term rather than permanent. Furthermore, RPOV only had a short-term positive response to the GDP shock in the 7th period. Although IRF was confirmed to be significant by the confidence interval, this effect was basically negligible. Therefore, we believe that the interaction of variables in the western region is mainly nonlinear.

In summary, financial inclusion development in the western region has effectively promoted poverty alleviation, but it has also widened income inequality to a certain extent. This conclusion remains robust under different regional samples, indicating that the mechanism of using financial inclusion to alleviate poverty is in line with China's economic development reality. Combined with the previous analysis, we also found that financial inclusion development in the western region has a stronger impetus to poverty alleviation, while economic growth has a significant inhibitory effect on income inequality. We did not find evidence in the previous literature that the miracle of poverty alleviation in China stemmed entirely from market-led economic growth [83], but that does not mean that we should deny the role that economic growth plays in tackling poverty. This is because poverty issues are often intertwined with issues such as income distribution and poverty alleviation policies, the poverty alleviation elasticity of economic growth changes dynamically in different periods, and the ultimate poverty alleviation effect will gradually weaken over time [79]. When the internal income gap is relatively serious, the poverty alleviation effect of economic growth will be greatly limited; that is, economic growth will not spontaneously benefit poor groups [111]. In addition, financial inclusion development did not have an impact on the economic growth of the western region, which is different from the conclusions of some scholars that financial inclusion contributes to economic growth [59]. In fact, if the development of financial inclusion only focuses on solving the contact exclusion of the poor—but cannot alleviate the use exclusion of key financial services such as credit funds—then the development of financial inclusion will not necessarily promote regional economic growth [35]. Therefore, in China's strategy to prevent the return of poverty, government departments should shift resources and policy focus to income inequality, and should no longer rely on the trickle-down effect of economic growth. Financial inclusion can become an important means of poverty governance in the future. The premise is to provide financial products that meet the needs of poor groups, to truly give full play to the inclusiveness of financial funds.

4.5. Analysis of Variance Decomposition. In order to investigate the impact of IFI, GDP, and GINI on RPOV, based on the impulse response analysis, this study further uses the variance decomposition (FEVDs) method to obtain the variance contribution rates of the impulse responses of different equations to the fluctuation of endogenous variables. Referring to the practice of Hailemariam et al. [84], we set the forecast period of variance decomposition to 10 years, and the results are shown in Table 5. At the national level, the fluctuation of RPOV in the first period was mainly caused by itself and GDP. The contribution rate of GDP was 2.4%, and the contribution rate of RPOV was as high as 97.6%. Later, it gradually decomposed into other variables. The fluctuation of RPOV in the tenth period was caused by itself and IFI. The contribution rate of RPOV was still as high as 62.8%; the contribution rate of IFI increased to 28.2%, and the contribution of GDP and GINI was relatively weak. From a regional perspective, the contribution rates of RPOV in the first period of the eastern, central, and western regions were 96%, 87.9%, and 99.8%, respectively, and the contribution rates of GDP in the same period were 4%, 12.1%, and 0.2%. Over time, the contribution rates of RPOV in the tenth period dropped to 81.8%, 36.7%, and 65.1%, and the contribution rates of IFI rose to 6.8%, 7%, and 31.8%. RPOV in each region is the main factor leading to its own changes throughout the forecast period, but the contribution of IFI has gradually increased over time. As mentioned above, on the one hand, the poverty problem has strong inertia, and the solution to the poverty problem requires a long-term process. On the other hand, financial inclusion has a time lag effect when it plays a role in poverty alleviation; that is, financial capital investment needs to go through a certain period before it can be transformed into the welfare of the poor. Finally, by comparing the mean values of variance contribution rates, we find that there is cross-regional

Table 5: Variance decomposition results of RPOV.

Period	GDP	RPOV	GINI	IFI
National				
1	0.024	0.976	0.000	0.000
2	0.014	0.940	0.016	0.029
3	0.011	0.886	0.025	0.078
4	0.009	0.825	0.026	0.139
5	0.010	0.762	0.025	0.204
6	0.013	0.704	0.023	0.260
7	0.019	0.659	0.023	0.298
8	0.029	0.632	0.026	0.313
9	0.040	0.624	0.032	0.305
10	0.051	0.628	0.039	0.282
Mean	0.022	0.764	0.024	0.191
Eastern				
1	0.040	0.960	0.000	0.000
2	0.057	0.925	0.006	0.012
3	0.055	0.912	0.014	0.018
4	0.064	0.888	0.020	0.028
5	0.089	0.849	0.023	0.040
6	0.124	0.802	0.023	0.051
7	0.162	0.757	0.021	0.059
8	0.196	0.721	0.018	0.065
9	0.223	0.694	0.016	0.067
10	0.243	0.676	0.014	0.068
Mean	0.125	0.818	0.016	0.041
Central				
1	0.121	0.879	0.000	0.000
2	0.087	0.851	0.053	0.009
3	0.131	0.749	0.103	0.017
4	0.190	0.628	0.154	0.027
5	0.251	0.518	0.193	0.038
6	0.299	0.438	0.215	0.048
7	0.332	0.388	0.224	0.056
8	0.350	0.365	0.223	0.062
9	0.357	0.360	0.216	0.067
10	0.357	0.367	0.207	0.070
Mean	0.248	0.554	0.159	0.039
Western				
1	0.002	0.998	0.000	0.000
2	0.001	0.942	0.002	0.054
3	0.002	0.844	0.010	0.143
4	0.012	0.730	0.022	0.236
5	0.033	0.620	0.036	0.312
6	0.062	0.531	0.047	0.359
7	0.095	0.474	0.055	0.376
8	0.125	0.449	0.057	0.368
9	0.147	0.452	0.056	0.345
10	0.159	0.471	0.052	0.318
Mean	0.064	0.651	0.034	0.251

The values in the table are the results of 1000 simulations using the Monte Carlo method. Due to space limitations, only the variance decomposition results of the RPOV variables are reported in the table.

heterogeneity in the dynamic effects of endogenous variables on poverty alleviation. The intensity of the impact of IFI on RPOV is followed by the western region (25.1%), eastern region (4.1%), and central region (3.9%); the impact on GDP is followed by the central region (24.8%), eastern region (12.5%), and western region (6.4%); the impact on GINI is followed by the central region (15.9%), western region (3.4%), and eastern region (1.6%). Overall, China's financial inclusion development system is still in its infancy, and there is still much room for expansion in the depth and breadth of financial inclusion development.

4.6. Robustness Check. In previous empirical results, the relationship between IFI and RPOV maintained a consistent conclusion, which can be regarded as robust to a certain

extent. However, although the PVAR model does not need to consider potential endogeneity issues, it treats all variables in the system as endogenous variables, resulting in empirical results that may be affected by the ordering of endogenous variables. Specifically, the orthogonalized IRF values may change due to the order of the endogenous variables in the Cholesky decomposition, and the variables ranked in the front will have a shock to the variables in the rear, but the variables in the rear may only affect the variables in the front, causing the final shock effect to lag by one cycle. Therefore, Abrigo and Love [80] suggested re-ordering endogenous variables in the PVAR model based on the results of the Granger causality test, and performing robustness tests on the results of the IRF and variance decomposition. Based on this, we found that there is a complex reverse causal relationship between endogenous variables, and it is still impossible to determine the lead-lag order of variables. Finally, this article re-establishes the PVAR model following the component order under poverty decomposition theory; that is, the variable order is set as GINI $\longrightarrow$ GDP $\longrightarrow$ IFI $\longrightarrow$ RPOV. The results of the robustness test are shown in Figure 6. Due to space limitations, Figure 6 only reports the IRF of IFI to RPOV in each region and the variance decomposition results of RPOV (we have not reported all the robustness test results, which are retained by the authors for request). From the impulse response graph, we can see that the response amplitudes of the national, eastern, central, and western regions are highly consistent with previous results, and the direction of the impact has not changed. From the variance decomposition diagram, RPOV is still the main factor causing its own fluctuations, and the contribution of IFI gradually increases over time and the impact of IFI on RPOV in the western region is still the highest. In summary, the empirical results of this article are robust.

5. Time-Varying Nonparametric Estimates

The point estimates from the PVAR model help identify the average impact of endogenous explanatory variables on RPOV, but the regression coefficient cannot capture the difference in the impact of financial inclusion policies before and after the Chinese government's official inclusion of the support program in 2015. Although some scholars have tried to compare the impact difference at different time points through IRF, such as applied data from the pre- and post-COVID-19 periods to discuss the impact of oil prices on the stock market [105]. But as we have discussed in Section 3.2, some scholars have questioned this research design. According to Chai et al. [112], standard PVAR models with fixed parameters only allow nonlinear effects between variables to be described by IRF, provided that the regression coefficients do not change over different periods of IRF. However, the results of the IRF may be inaccurate due to the time-varying state of the variables. Therefore, we re-estimated the time-varying effects of endogenous explanatory variables on RPOV using the LLDVE-based NP-TVP method and obtained the standard errors of the time-varying regression coefficients using the Monte Carlo simulation (1000 times) method. Figure 7 shows the time-varying nonparametric estimation results of RPOV by IFI, the gray range represents the 95% confidence interval of the time-varying regression coefficient, and the dashed line in the figure represents the key node in 2015; because the financial inclusion develops vigorously after China's State Council's "Government Work Report" in 2015, we are more concerned with the time-varying effect of IRF on RPOV in this article. We found that the effect of IFI on RPOV remained negative at the national level and in the eastern, central, and western regions, and the confidence intervals of the regression coefficients did not contain 0 in most years, indicating that the effect of IFI on RPOV was statistically significant.

As shown in Figure 7, the estimation results of NP-TVP not only confirmed that the influence of IFI on RPOV was time-varying, but also meant that the influence of IFI on RPOV was nonlinear in each region. Specifically, from a national perspective, the impact of IFI on RPOV was −0.003 in 2004, and the absolute value of the regression coefficient reached its maximum value (−0.021) in 2015. The marginal effect of IFI has been increasing until 2015, and after 2015, the marginal effect value has resumed a gradual downward trend. In the eastern region, the minimum value of the impact of IFI on RPOV (−0.002) also occurred in 2004, and although there was a slight fluctuation in the value of the marginal effect of IFI in the first 3 years, the marginal effect then rose rapidly and reached a maximum value (−0.008) in 2013; after 2015, its marginal impact resumed the trend of gradual attenuation. For the central region, the marginal impact of IFI on RPOV also showed a trend of increasing first and then decreasing. The minimum value of the absolute value of the regression coefficient (−0.004) appeared in 2004 and reached the maximum value (−0.020) in 2013. In the western region, the trend of the marginal impact of IFI on RPOV is completely consistent with that of other regions. The absolute value of the regression coefficient was the smallest (−0.003) in 2004, and the maximum value (−0.037) of the marginal impact appeared in 2016. Therefore, the results of NP-TVP imply that the influence of IFI on RPOV presents a positive U-shaped feature, which is consistent with the conclusion obtained from IRF within the framework of PVAR. Interestingly, this article finds that around 2015 may be an inflection point for the marginal impact of IFI on RPOV. In other words, the marginal impact of IFI has been increasing until 2015, and the marginal impact of IFI has been decreasing after 2015.

Based on the opinions in the previous literature, we believe that there may be three reasons for the above changes. Firstly, an important factor is that the Chinese government has been accelerating progress of achieving the poverty control target. Since reform and opening-up in 1978, the Chinese government has been working hard to eradicate poverty. For example, the poverty rate dropped from 94% in 1981 to 4% in 2014 [113]. Especially in the last 20 years, the eradication of absolute poverty by 2020 has become a task that governments at all levels must complete and before 2015 is a critical period for poverty governance. Local officials will use various administrative measures or political resources to speed up the poverty governance process [114], and specific

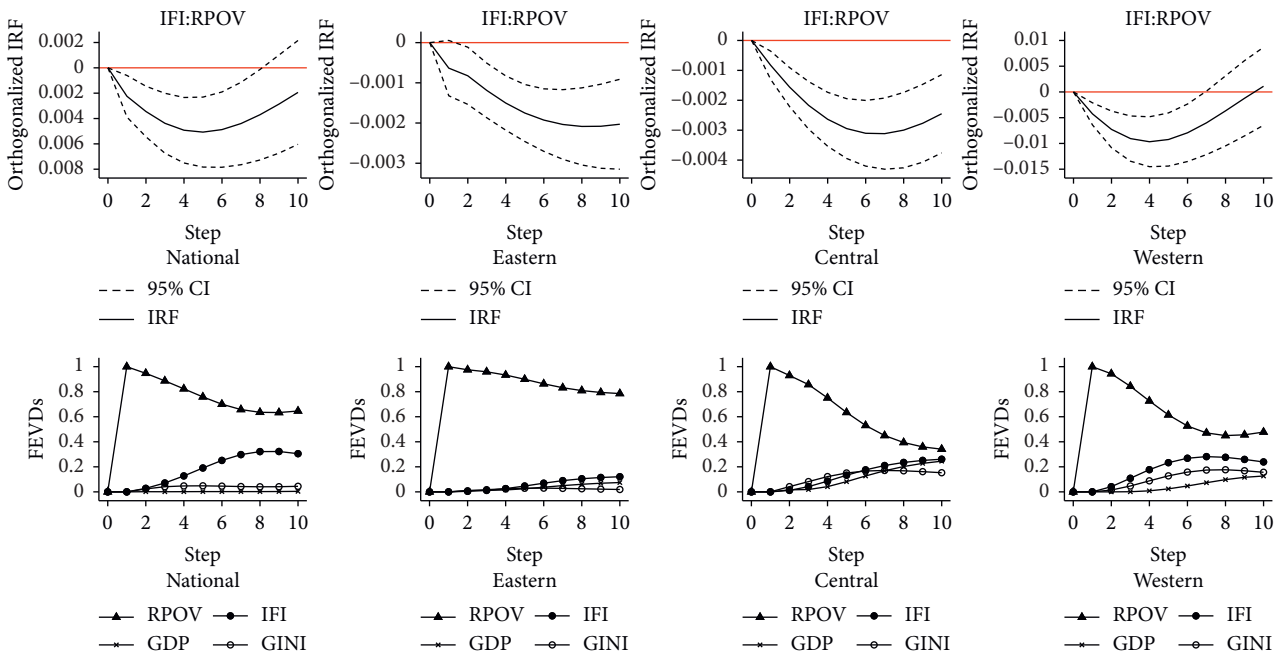

Figure 6: Robustness test (adjusting variable order).

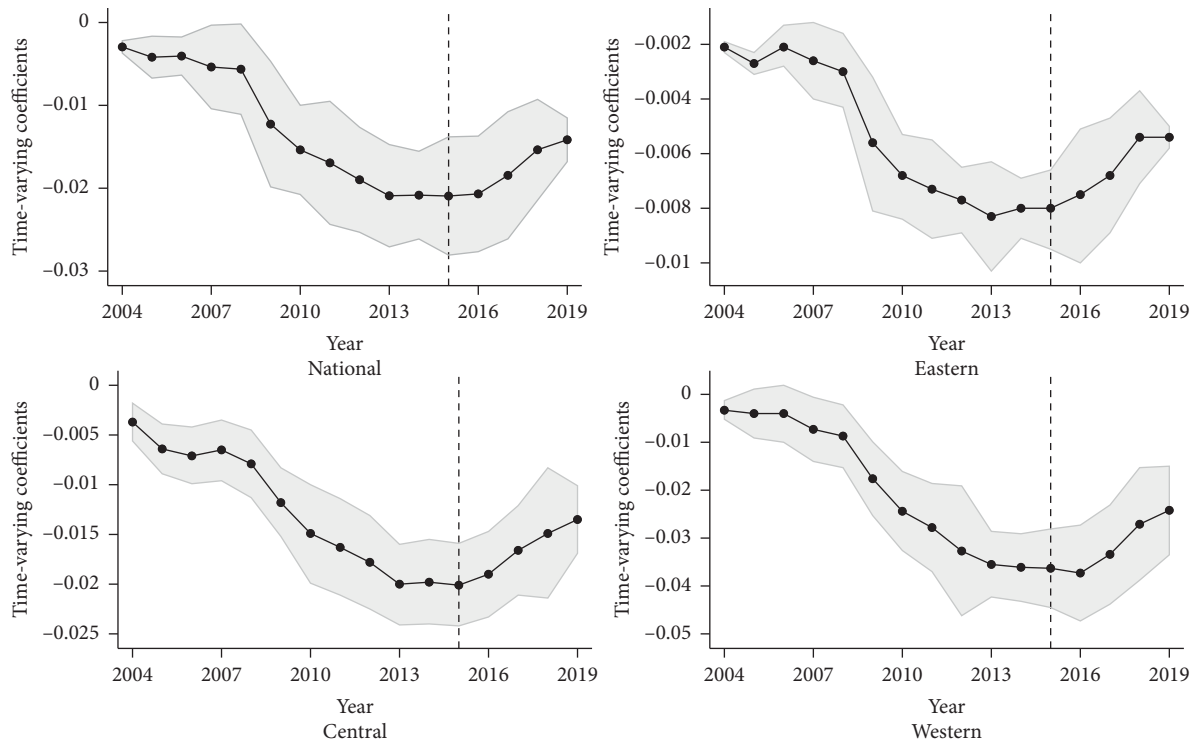

Figure 7: Nonparametric time-varying coefficient estimation results.

poverty alleviation measures include vocational education and training, helping cadres' residencies in impoverished villages, microfinance, and poverty alleviation resettlement [115]. Therefore, the speed of poverty alleviation continued to accelerate before 2015, which also means that any poverty reduction path may effectively release the poverty reduction effect. Secondly, the State Council proposed to vigorously develop inclusive finance late, so it is difficult to produce obvious policy effects in the short term. Although China's, the State Council's "Government Work Report" in 2015 programs to vigorously develop financial inclusion, but financial inclusion has been widespread in China in various

forms. In fact, as described in our review of the literature, the United Nations advocated for governments to implement financial inclusion systems as early as 2005. However, China only officially included financial inclusion in the official document in 2015, and the full release of the policy effects usually takes some time. In addition, due to the sharp decline in the number of poor people in China after 2015, even if inclusive finance welcomes new development opportunities, the marginal effect on poverty will be difficult to show. Therefore, the policy effects of financial inclusion may be more pronounced in other ways, such as its role in promoting household consumption and diversity of consumption, which have been documented in the literature [116–118]. Finally, some scholars have tried to use the marginal utility theory to explain the impact of IFI on RPOV. They believe that the marginal impact of IFI on RPOV essentially increases first and then decreases [119, 120], similar to the Kuznets curve in development economics. However, to the best of our knowledge, these views are based on theoretical analysis. This article uses PVAR and NP-TVP methods to carry out empirical analysis from a nonlinear perspective, which further verifies the rationality of these conclusions.

6. Conclusions

Based on the poverty decomposition theory, this study puts financial inclusion development, economic growth, income inequality, and poverty alleviation in a unified PVAR model analysis framework and uses the balanced panel data of 30 provinces in China from 2004 to 2019 to reveal the direction and intensity of the impact of various factors on poverty alleviation in the different regions of China. The research findings are as follows. Firstly, financial inclusion development in China has a significant role in promoting poverty alleviation. This conclusion has strong robustness in empirical analysis in different regions, indicating that the mechanism of using financial inclusion to promote poverty alleviation is in line with the reality of China's economic development. Secondly, in general, the poverty problem shows strong inertia over time. During the inspection period, the role of economic growth in poverty alleviation is relatively limited, and financial inclusion development is the factor that contributes the most to poverty alleviation. Thirdly, the nonlinear linkage effect among the factors is significant. Financial inclusion development has a positive U-shaped impact on poverty alleviation and an inverted U-shaped impact on income inequality, indicating that the poverty alleviation effect of financial inclusion has the law of diminishing marginal utility. Fourth, there is spatial heterogeneity in the impact of financial inclusion and economic growth on poverty alleviation. Financial inclusion development has the strongest effect on poverty alleviation in the western regions, while the improvement effect of economic growth on poverty alleviation is more significant in the central and eastern regions, reflecting that each region has different economic paths in achieving poverty alleviation. Finally, although the development of financial inclusion can effectively promote poverty alleviation, income inequality offsets part of the poverty alleviation effect. In the future, financial inclusion policies must pay more attention to the benefits of poor groups.

Based on the above research conclusions, this article proposes the following policy implications. Firstly, actively promote the formation of stable policy goals for China's financial inclusion service system. Financial inclusion policies should strictly implement the targeting of small and microenterprises, farmers, urban low-income people, poor people, disabled people, the elderly, and other special groups and build a financial inclusion system that is beneficial to the poor through the guidance of the government and the market, so that the financial system is gradually adjusted and improved considering the policy effects. In practice, it is necessary to avoid the target deviation caused by the "financial exclusion" problem under complete market dominance and to also prevent the risk of financial asset loss that may be caused by excessive government intervention. Secondly, broaden the supply channels of financial inclusion products and services. China's financial inclusion system is still dominated by state-owned banks. Due to the limited repayment ability of poor groups, traditional credit channels have been unable to meet market demand. Policy departments should encourage banks and other formal financial institutions and private informal financial institutions to innovate financial service models, develop new products, such as microfinance and Internet finance, and promote digital service methods, such as "online intelligent approval," to improve financial inclusion. Thirdly, the policy orientation on poverty governance should focus on improving income distribution. It is worth noting that the contribution of economic growth to poverty alleviation in the western regions has weakened, and general economic growth has been unable to play a role in poverty alleviation. While stabilizing economic growth, government departments must not only promote the transformation of the growth mode to a type of economic growth that benefits the poor, but must also correct the discriminatory allocation of funds between the rich and the poor, and reduce the negative impact of income inequality on the effectiveness of financial inclusion in poverty alleviation. Finally, implementation of a differentiated financial inclusion development strategy. For the economically underdeveloped central and western regions, the focus should be on improving the breadth of financial services, focusing on improving the penetration and convenience of financial services by increasing the delivery of various financial service points. For the economically developed eastern region, more attention should be paid to improving the utility of financial services, strengthening the ratio of financial services to poor groups by formal institutions and ensuring that poor groups can obtain the financial services they need in a reasonable way. Essentially, promoting the financial inclusion system according to local conditions and paying attention to improving institutional

conditions will help China's economy develop in a balanced way, improve income inequality, and realize a poverty alleviation path that takes into account fairness and efficiency.

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 there is no conflict of interest regarding the publication of this article.

Authors' Contributions

Z. Chen and H. Zhu conceived the study. Z. Chen helped with the methodology and software. Z. Chen, H. Zhu, B. Cao, and W. Zhao validated the study. Z. Chen performed the formal analysis. B. Cao and Y. Cai investigated the study. H. Zhu helped with resources. Z. Chen, Y. Cai, and W. Zhao curated the data. Z. Chen prepared the original draft of the manuscript and reviewed and edited the manuscript. Z. Chen, W. Zhao, and B. Cao carried out visualization. H. Zhu supervised the study and helped with project administration and funding acquisition. All the authors have read and agreed to the published version of the manuscript.

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References

[1] E. Makarenko, L. Nivorozhkina, A. Tregubova, T. Toropova, and E. Nazarova, "Risk of increasing income inequality and poverty: analysis by income source," *Sustainability*, vol. 14, no. 3, p. 1610, 2022.

[2] United Nations Department of Economic and Social Affairs, "Transforming our world: the 2030 agenda for sustainable development," 2022, https://sdgs.un.org/2030agenda.

[3] J. Xi, "Speech at the national poverty alleviation review and commendation conference," *Bulletin of The State Council of the People's Republic of China*, vol. 7, pp. 5–11, 2021.

[4] L. Hu, S. Yao, and X. Song, "The assessment of China's weak relative poverty and its enlightenment to the poverty reduction strategy after 2020," *Chinese Rural Economy*, vol. 1, pp. 72–90, 2021.

[5] Z. Yin and D. Zhang, "Financial inclusion, household poverty and vulnerability," *China Economic Quarterly*, vol. 20, no. 5, pp. 153–172, 2020.

[6] Y. Li and K. Shen, "The structure of financial expenditure, relative poverty and economic growth," *Management World*, vol. 11, pp. 14–26, 2007.

[7] N. M. Odhiambo, "Finance-growth-poverty nexus in South Africa: a dynamic causality linkage," *The Journal of Socio-Economics*, vol. 38, no. 2, pp. 320–325, 2009.

[8] A. Dhrifi, "Financial development and the "Growth-Inequality-Poverty" triangle," *Journal of the knowledge economy*, vol. 6, no. 4, pp. 1163–1176, 2015.

[9] M. S. A. Majid, S. Dewi, Aliasuddin, and S. H. Kassim, "Does financial development reduce poverty? Empirical evidence from Indonesia," *Journal of the knowledge economy*, vol. 10, no. 3, pp. 1019–1036, 2019.

[10] A. Erlando, F. D. Riyanto, and S. Masakazu, "Financial inclusion, economic growth, and poverty alleviation: evidence from eastern Indonesia," *Heliyon*, vol. 6, no. 10, Article ID e05235, 2020.

[11] S. Dewi, M. S. Abd Majid, S. Kassim, and S. Kassim, "Dynamics of financial development, economic growth, and poverty alleviation: the Indonesian experience," *South East European Journal of Economics and Business*, vol. 13, no. 1, pp. 17–30, 2018.

[12] L. Zhou, J. Liao, and H. Zhang, "Digital financial inclusion, credit availability and household poverty: evidence from a micro-level survey," *Economic Science*, vol. 1, pp. 145–157, 2021.

[13] J. Li, Y. Peng, and S. Ma, "Inclusive finance and economic development in China: multidimensional connotation and empirical analysis," *Economic Research Journal*, vol. 55, no. 4, pp. 37–52, 2020.

[14] C. Y. Park and R. J. R. Mercado, "Financial inclusion, poverty, and income inequality," *Singapore Economic Review*, vol. 63, no. 01, pp. 185–206, 2018.

[15] Z. Yin, C. Peng, and A. Leon, "The development and influence of Family inclusive finance in China," *Management World*, vol. 35, no. 2, pp. 74–87, 2019.

[16] F. Donou-Adonsou and K. Sylwester, "Financial development and poverty reduction in developing countries: new evidence from banks and microfinance institutions," *Review of development finance*, vol. 6, no. 1, pp. 82–90, 2016.

[17] N. Kaidi and S. Mensi, "Financial development, income inequality, and poverty reduction: democratic versus autocratic countries," *Journal of the knowledge economy*, vol. 11, no. 4, pp. 1358–1381, 2019.

[18] A. V. Banerjee and A. F. Newman, "Occupational choice and the process of development," *Journal of Political Economy*, vol. 101, no. 2, pp. 274–298, 1993.

[19] L. Li and S. Bian, "Economic growth, income distribution and poverty: identification and decomposition of inclusive growth," *Economic Research Journal*, vol. 56, no. 2, pp. 54–70, 2021.

[20] J. Li and X. Han, "The effect of financial inclusion on income distribution and poverty alleviation: policy framework selection for efficiency and equity," *Journal of Financial Research*, vol. 3, pp. 129–148, 2019.

[21] H. Landreth and D. C. Colander, *History of Economic Thought*, South-Western College Pub, Cincinnati, Ohio, OH, USA, 2001.

[22] R. I. McKinnon, *Money and Captial in Economic Development*, Brookings Institution Press, Washington D.C., USA, 1973.

[23] E. Detragiache, A. Abiad, and T. Tressel, "A new database of financial reforms," *IMF Working Papers*, vol. 8, no. 266, pp. 281–302, 2008.

[24] A. Mialou, G. Amidzic, and A. Massara, "Assessing countries' financial inclusion standing: a new composite index," *Journal of Banking and Financial Economics*, vol. 2/2017, no. 8, pp. 105–126, 2017.

[25] M. Chibba, "Financial inclusion, poverty reduction and the millennium development goals," *European Journal of Development Research*, vol. 21, no. 2, pp. 213–230, 2009.

[26] M. Sarma and J. Pais, "Financial inclusion and development," *Journal of International Development*, vol. 23, no. 5, pp. 613–628, 2011.

[27] K. S. Imai and M. S. Azam, "Does microfinance reduce poverty in Bangladesh? New evidence from household panel data," *Journal of Development Studies*, vol. 48, no. 5, pp. 633–653, 2012.

[28] J. Boukhatem, "Assessing the direct effect of financial development on poverty reduction in a panel of low- and middle-income countries," *Research in International Business and Finance*, vol. 37, pp. 214–230, 2016.

[29] I. Koomson, R. A. Villano, and D. Hadley, "Effect of financial inclusion on poverty and vulnerability to poverty: evidence using a multidimensional measure of financial inclusion," *Social Indicators Research*, vol. 149, no. 2, pp. 613–639, 2020.

[30] R. Gutiérrez-Romero and M. Ahamed, "COVID-19 response needs to broaden financial inclusion to curb the rise in poverty," *World Development*, vol. 138, Article ID 105229, 2021.

[31] X. Zheng and Y. Zhu, "Financial inclusion, economic opportunity and poverty reduction," *World Economic Papers*, vol. 1, pp. 101–120, 2019.

[32] J. Sun, K. Han, and J. Hu, "Can digital finance reduce relative poverty: evidence from CHFS data," *Collected Essays on Finance and Economics*, vol. 12, pp. 50–60, 2020.

[33] D. James, "Deeper into a hole? Borrowing and lending in South Africa," *Current Anthropology*, vol. 55, no. S9, pp. 17–29, 2014.

[34] P. Mader, "Contesting Financial Inclusion," *Development and Change*, vol. 49, no. 2, pp. 461–483, 2018.

[35] W. Wang and Y. Zhu, "Inclusive finance and county capital outflow:poverty alleviation or worsen," *Economic Theory and Business Management*, vol. 1, pp. 98–108, 2018.

[36] N. Guo, "Financial liberalization and variation in China's resident consumption propensity," *China Economic Quarterly*, vol. 17, no. 4, pp. 1361–1382, 2018.

[37] Z. He, X. Zhang, and G. Wan, "Digital finance, digital divide, and multidimensional poverty," *Statistical Research*, vol. 37, no. 10, pp. 79–89, 2020.

[38] D. Shan and C. Zheng, "A review on the micro-mechanism and influencing factors of poverty alleviation effect of economic development mode," *Inquiry into Economic Issues*, vol. 11, pp. 161–166, 2012.

[39] D. Zhao, "Cyclic feedback mechanism of poverty trap and anti-poverty intervention path," *Journal of Shanghai Jiaotong University*, vol. 28, no. 6, pp. 9–15, 2020.

[40] P. Zhong, "Economical explanation of the historical achievement in poverty elimination in rural China," *Issues in Agricultural Economy*, vol. 5, pp. 4–11, 2021.

[41] J. G. Montalvo and M. Ravallion, "The pattern of growth and poverty reduction in China," *Journal of Comparative Economics*, vol. 38, no. 1, pp. 2–16, 2010.

[42] A. Michalek and J. Výbošťok, "Economic growth, inequality and poverty in the EU," *Social Indicators Research*, vol. 141, no. 2, pp. 611–630, 2019.

[43] D. Dollar, T. Kleineberg, and A. Kraay, "Growth still is good for the poor," *European Economic Review*, vol. 81, pp. 68–85, 2016.

[44] M. Ravallion, *The Economics of Poverty: History, Measurement, and Policy*, Oxford University Press, New York, NY, USA, 2016.

[45] R. H. Adams, "Economic growth, inequality and poverty: estimating the growth elasticity of poverty," *World Development*, vol. 32, no. 12, 2004.

[46] M. Ravallion and S. Chen, "What can new survey data tell us about recent changes in distribution and poverty?" *The World Bank Economic Review*, vol. 11, no. 2, pp. 357–382, 1997.

[47] R. Eastwood and M. Lipton, "Pro-poor growth and pro-growth poverty reduction: meaning, evidence, and policy implications," *Asian Development Review*, vol. 18, no. 2, pp. 22–58, 2000.

[48] D. Malerba, "The trade-off between poverty reduction and carbon emissions, and the role of economic growth and inequality: an empirical cross-country analysis using a novel indicator," *Social Indicators Research*, vol. 150, no. 2, pp. 587–615, 2020.

[49] J. D. Moore and J. A. Donaldson, "Human-scale economics: economic growth and poverty reduction in northeastern Thailand," *World Development*, vol. 85, pp. 1–15, 2016.

[50] J. A. Schumpeter and R. Opie, *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*, Oxford University Press, London, UK, 1961.

[51] R. E. Lucas, "On the mechanics of economic development," *Journal of Monetary Economics*, vol. 22, no. 1, pp. 3–42, 1988.

[52] M. H. Miller, "Financial markets and economic growth," *The Journal of Applied Corporate Finance*, vol. 24, no. 1, pp. 8–13, 2012.

[53] R. G. King and R. Levine, "Finance and growth: schumpeter might be right," *Quarterly Journal of Economics*, vol. 108, no. 3, pp. 717–737, 1993.

[54] M. N. A. Siddik, T. Ahsan, and S. Kabiraj, "Does financial permeation promote economic growth? Some econometric evidence from asian countries," *Sage Open*, vol. 9, no. 3, Article ID 215824401986581, 2019.

[55] M. Sarma, "Measuring financial inclusion," *Economics Bulletin*, vol. 35, no. 1, pp. 604–611, 2015.

[56] N. U. Ain, S. Sabir, and N. Asghar, "Financial inclusion and economic growth: empirical evidence from selected developing economies," *Review of Economics and Development Studies*, vol. 6, no. 1, pp. 179–203, 2020.

[57] Y. Huang and Y. Zhang, "Financial inclusion and urban-rural income inequality: long-run and short-run relationships," *Emerging Markets Finance and Trade*, vol. 56, no. 2, pp. 457–471, 2020.

[58] R. Huang, S. Kale, S. R. Paramati, and F. Taghizadeh-Hesary, "The nexus between financial inclusion and economic development: comparison of old and new EU member

countries," *Economic Analysis and Policy*, vol. 69, pp. 1–15, 2021.

[59] M. W. Adedokun and M. Ağa, "Financial inclusion: a pathway to economic growth in Sub-Saharan African economies," *International Journal of Finance & Economics*, vol. 26, pp. 1–17, 2021.

[60] H. Qian, Y. Tao, S. Cao, and Y. Cao, "Theoretical and empirical analysis on the development of digital finance and economic growth in China," *The Journal of Quantitative & Technical*, vol. 37, no. 6, pp. 26–46, 2020.

[61] C. Chu, M. Tong, Y. Li, and W. Fei, "China's digital inclusive finance and provincial economic growth: empirical research based on spatial econometric model," *Inquiry into Economic Issues*, vol. 6, pp. 179–190, 2021.

[62] D. Singh and N. Stakic, "Financial inclusion and economic growth nexus: evidence from SAARC countries," *South Asia Research*, vol. 41, no. 2, pp. 238–258, 2021.

[63] M. Usman, M. S. A. Makhdum, and R. Kousar, "Does financial inclusion, renewable and non-renewable energy utilization accelerate ecological footprints and economic growth? Fresh evidence from 15 highest emitting countries," *Sustainable Cities and Society*, vol. 65, Article ID 102590, 2020.

[64] M. Kar, Ş. Nazlıoğlu, and H. Agir, "Financial development and economic growth nexus in the MENA countries: bootstrap panel granger causality analysis," *Economic Modelling*, vol. 28, no. 1–2, pp. 685–693, 2011.

[65] M. Nili and M. Rastad, "Addressing the growth failure of the oil economies: the role of financial development," *The Quarterly Review of Economics and Finance*, vol. 46, no. 5, pp. 726–740, 2007.

[66] P. K. Narayan and S. Narayan, "The short-run relationship between the financial system and economic growth: new evidence from regional panels," *International Review of Financial Analysis*, vol. 29, pp. 70–78, 2013.

[67] M. Ali, S. H. Hashmi, M. R. Nazir, A. Bilal, and M. I. Nazir, "Does financial inclusion enhance economic growth? Empirical evidence from the IsDB member countries," *International Journal of Finance & Economics*, vol. 26, no. 4, pp. 5235–5258, 2021.

[68] Y. Zhu, S. Bashir, and M. Marie, "Assessing the relationship between poverty and economic growth: does sustainable development goal can be achieved," *Environmental Science and Pollution Research*, vol. 29, no. 19, pp. 27613–27623, 2022.

[69] A. T. Bui, C. V. Nguyen, and T. P. Pham, "Poverty among ethnic minorities: the transition process, inequality and economic growth," *Applied Economics*, vol. 49, no. 31, pp. 3114–3128, 2017.

[70] M. A. Omar and K. Inaba, "Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis," *Journal of economic structures*, vol. 9, no. 1, pp. 37–25, 2020.

[71] G. Datt and M. Ravallion, "Growth and redistribution components of changes in poverty measures: a decomposition with applications to Brazil and India in the 1980s," *Journal of Development Economics*, vol. 38, no. 2, pp. 275–295, 1992.

[72] N. Kakwani, "On measuring growth and inequality components of poverty with application to Thailand," *Journal of Quantitative Economics*, vol. 16, no. 1, pp. 67–80, 2000.

[73] J. H. Kim, "A study on the effect of financial inclusion on the relationship between income inequality and economic growth," *Emerging Markets Finance and Trade*, vol. 52, no. 2, pp. 498–512, 2016.

[74] C. Wang, G. Wan, and L. Lin, "The impacts of growth and inequality on poverty reduction," *Journal of Agrotechnical Economics*, vol. 10, pp. 22–37, 2021.

[75] C. Y. Park and R. V. Mercado, "Financial inclusion, poverty, and income inequality in developing Asia," in *Financial Inclusion in Asia. Palgrave Studies in Impact Finance*, S. Gopalan and T. Kikuchi, Eds., Palgrave Macmillan, London, 2015.

[76] A. A. Agyemang-Badu, K. Agyei, and E. K. Duah, "Financial inclusion, poverty and income inequality: evidence from africa," *Spiritan International Journal of Poverty Studies*, vol. 2, no. 2, pp. 1–19, 2018.

[77] I. Ouechtati, "The contribution of financial inclusion in reducing poverty and income inequality in developing countries," *Asian Economic and Financial Review*, vol. 10, no. 9, pp. 1051–1061, 2020.

[78] A. M. Balisacan and N. Fuwa, "Growth, inequality and politics revisited: a developing-country case," *Economics Letters*, vol. 79, no. 1, pp. 53–58, 2003.

[79] C. Luo, "Economic growth, inequality and poverty in rural China," *Economic Research Journal*, vol. 47, no. 2, pp. 15–27, 2012.

[80] M. R. M. Abrigo and I. Love, "Estimation of panel vector autoregression in Stata," *STATA Journal: Promoting communications on statistics and Stata*, vol. 16, no. 3, pp. 778–804, 2016.

[81] A. Adarov, "Dynamic interactions between financial cycles, business cycles and macroeconomic imbalances: a panel VAR analysis," *International Review of Economics & Finance*, vol. 74, pp. 434–451, 2021.

[82] M. M. Rahman, "The dynamic nexus of energy consumption, international trade and economic growth in BRICS and ASEAN countries: a panel causality test," *Energy*, vol. 229, Article ID 120679, 2021.

[83] G. Wan, X. Hu, and W. Liu, "China's poverty reduction miracle and relative poverty: focusing on the roles of growth and inequality," *China Economic Review*, vol. 68, Article ID 101643, 2021.

[84] A. Hailemariam, T. Sakutukwa, and R. Dzhumashev, "Long-term determinants of income inequality: evidence from panel data over 1870-2016," *Empirical Economics*, vol. 61, no. 4, pp. 1935–1958, 2021.

[85] D. Li, J. Chen, and J. Gao, "Nonparametric time-varying coefficient panel data models with fixed effects," *The Econometrics Journal*, vol. 14, no. 3, pp. 387–408, 2011.

[86] S. Awaworyi Churchill, K. Ivanovski, and M. E. Munyanyi, "Income inequality and renewable energy consumption: time-varying nonparametric evidence," *Journal of Cleaner Production*, vol. 296, Article ID 126306, 2021.

[87] X. Ren, Z. Tong, X. Sun, and C. Yan, "Dynamic impacts of energy consumption on economic growth in China: evidence from a nonparametric panel data model," *Energy Economics*, vol. 107, Article ID 105855, 2022.

[88] Z. Chen, H. Zhu, and B. Cao, "Research on financial development, economic growth and energy consumption: based on ARDL-ECM model," *Journal of Technical Economics & Management*, no. 5, pp. 97–104, 2020.

[89] W. Tian, "Gini coefficient calculation and trend analysis of provincial residents' income," *Economic Science*, vol. 2, pp. 48–59, 2012.

[90] M. Sarma, "Measuring financial inclusion for asian economies," in *Financial Inclusion in Asia. Palgrave Studies in*

Impact Finance, S. Gopalan and T. Kikuchi, Eds., Palgrave Macmillan, London, UK, 2016.

[91] F. Allen, A. Demirguc-Kunt, L. Klapper, and M. S. M. Peria, "The foundations of financial inclusion: understanding ownership and use of formal accounts," *Journal of Financial Intermediation*, vol. 27, pp. 1–30, 2016.

[92] V. Pesqué-Cela, L. Tian, D. Luo, D. Tobin, and G. Kling, "Defining and measuring financial inclusion: a systematic review and confirmatory factor analysis," *Journal of International Development*, vol. 33, no. 2, pp. 316–341, 2021.

[93] X. Shi and Z. Xu, "Environmental regulation and firm exports: evidence from the eleventh Five-Year Plan in China," *Journal of Environmental Economics and Management*, vol. 89, pp. 187–200, 2018.

[94] S. Fan, S. Peng, and X. Liu, "Can smart city policy facilitate the low-carbon economy in China? A quasi-natural experiment based on pilot city," *Complexity*, vol. 2021, Article ID 9963404, 15 pages, 2021.

[95] H. Ke, S. Dai, and H. Yu, "Spatial effect of innovation efficiency on ecological footprint: city-level empirical evidence from China," *Environmental Technology & Innovation*, vol. 22, Article ID 101536, 2021.

[96] J. Liu, Q. Yu, Y. Chen, and J. Liu, "The impact of digital technology development on carbon emissions: a spatial effect analysis for China," *Resources, Conservation and Recycling*, vol. 185, Article ID 106445, 2022.

[97] S. Ren, Y. Hao, and H. Wu, "How does green investment A ect environmental pollution? Evidence from China," *Environmental and Resource Economics*, vol. 81, no. 1, pp. 25–51, 2022.

[98] Y. Luo, Z. Lu, M. Salman, and S. Song, "Impacts of heterogenous technological innovations on green productivity: an empirical study from 261 cities in China," *Journal of Cleaner Production*, vol. 334, Article ID 130241, 2021.

[99] R. Blundell and S. Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, vol. 87, no. 1, pp. 115–143, 1998.

[100] M. Koukouritakis, A. P. Papadopoulos, and A. Yannopoulos, "Transmission effects in the presence of structural breaks: evidence from South-Eastern European countries," *Economic Modelling*, vol. 41, pp. 298–311, 2014.

[101] X. Li and F. Luo, "Dynamic measurement analysis of urban innovation ability and ecological efficiency in China," *Complexity*, vol. 2022, Article ID 6049629, 14 pages, 2022.

[102] S. Jouida, "Diversification, capital structure and profitability: a panel VAR approach 1 1We are grateful to the editor and the anonymous reviewer for their valuable comments," *Research in International Business and Finance*, vol. 45, pp. 243–256, 2018.

[103] P. S. Chia, S. H. Law, I. Trinugroho, J. Wiwoho, S. M. Damayanti, and B. S. Sergi, "Dynamic linkages among transparency, income inequality and economic growth in developing countries: evidence from panel vector autoregressive (PVAR) model," *Research in International Business and Finance*, vol. 60, Article ID 101599, 2021.

[104] F. Peng and K. Zhan, "Over-debt, financial stress and economic downturn: theory and evidence," *China Economic Quarterly*, vol. 17, no. 4, pp. 1409–1426, 2018.

[105] T. T. Kumeka, D. C. Uzoma-Nwosu, and M. O. David-Wayas, "The effects of COVID-19 on the interrelationship among oil prices, stock prices and exchange rates in selected oil exporting economies," *Resources Policy*, vol. 77, Article ID 102744, 2022.

[106] W. Enders, *Applied Econometric Time Series*, John Wiley & Sons, New Jersey, NY, USA, 2014.

[107] N. Maurer and S. Haber, "Related lending and economic performance: evidence from Mexico," *The Journal of Economic History*, vol. 67, no. 3, pp. 551–581, 2007.

[108] D. M. TurEgano and A. G. Herrero, "Financial inclusion, rather than size, is the key to tackling income inequality," *Singapore Economic Review*, vol. 63, no. 1, pp. 167–184, 2018.

[109] J. Li, "The development of inclusive finance and the adjustment of urban-rural income distribution imbalance: an empirical study based on spatial econometric model," *Studies of International Finance*, vol. 10, pp. 14–23, 2017.

[110] H. Chen, G. Chen, X. Wei, L. Peng, and X. Zhang, "Effect of digital inclusive finance on increasing rural income and reducing poverty: empirical analysis based on inter-provincial panel data," *Economic Geography*, vol. 41, no. 3, pp. 184–191, 2021.

[111] H. H. Son and N. Kakwani, "Global estimates of pro-poor growth," *World Development*, vol. 36, no. 6, pp. 1048–1066, 2008.

[112] S. Chai, W. Chu, Z. Zhang, Z. Li, and M. Z. Abedin, "Dynamic nonlinear connectedness between the green bonds, clean energy, and stock price: the impact of the COVID-19 pandemic," *Annals of Operations Research*, pp. 1–28, 2022.

[113] S. Chen and M. Ravallion, "Reconciling the conflicting narratives on poverty in China," *Journal of Development Economics*, vol. 153, Article ID 102711, 2021.

[114] Z. Wang and S. Guo, "Politics of poverty governance: an introduction," *Journal of Chinese Political Science*, vol. 27, no. 2, pp. 205–219, 2022.

[115] J. Tang, J. Gong, W. Ma, and D. B. Rahut, "Narrowing urban-rural income gap in China: the role of the targeted poverty alleviation program," *Economic Analysis and Policy*, vol. 75, pp. 74–90, 2022.

[116] J. T. Lai, I. K. M. Yan, X. Yi, and H. Zhang, "Digital financial inclusion and consumption smoothing in China," *China and World Economy*, vol. 28, no. 1, pp. 64–93, 2020.

[117] Y. Li, H. Long, and J. Ouyang, "Digital financial inclusion, spatial spillover, and household consumption: evidence from China," *Complexity*, vol. 2022, Article ID 8240806, pp. 1 14, 2022.

[118] M. Chakrabarty and S. Mukherjee, "Financial inclusion and household welfare: an entropy-based consumption diversification approach," *European Journal of Development Research*, vol. 34, no. 3, pp. 1486–1521, 2022.

[119] Y. Wang and B. Zhao, "Research on the multidimensional poverty alleviation effect of inclusive finance—from the perspective of relative poverty," *Science & Technology and Economy*, vol. 34, no. 1, pp. 51–55, 2021.

[120] G. He, Z. Geng, and H. Pu, "Digital financial inclusion and sustainable poverty reduction: evidence from countries along the "belt and road"," *Journal of Northeastern University*, vol. 24, no. 3, pp. 22–31, 2022.

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Research Article

An Empirical Study of Macroeconomic Factors and Stock Returns in the Context of Economic Uncertainty News Sentiment Using Machine Learning

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Stock markets accurately reflect countries' economic health, and stock returns are tightly related to economic indices. One popular area of financial research is the factors that influence stock returns. Several investigations have frequently cited macroeconomic factors, among numerous elements. Therefore, this study focuses on the empirical analysis of the relationship between macroeconomic factors and stock market returns. When a stock market becomes increasingly volatile, it becomes susceptible to economic uncertainty news, and information on social media platforms. Thus, we incorporated a new dimension of economic uncertainty news sentiment (EUNS) for stock return predictions. We employed the daily data ofgold index, crude oil price, interest rate, exchange rate, and stock returns for a set of countries from January 2010 to December 2020. Subsequently, to compute coefficients, we conducted a regression analysis using one of the more sophisticated approaches: single-layer neural networks and ordinary least square regression. In addition, we only computed EUNS for the period of the fiscal budget announcement for the US, Turkey, and Hong Kong. The results indicate that the gold index, interest rate, and exchange rate are highly significant and negative macroeconomic factors for all analyzed countries. These findings also indicate that EUNS is important and detrimental for projecting stock returns.

1. Introduction

In today's global world, stock market performance is quite crucial for economic stability and growth. On the other hand, stock markets are also sensitive to economic conditions and uncertain events. Economists contend that the stock market is a leading indicator of economic growth. When the stock market does well, it indicates that the economy is working according to plan. For instance, it is indicated in existing studies that there have been positive influences on the economic growth of countries caused by the capitalization of stock markets [1]. Moreover, it has also been well-researched that several macroeconomic factors, business financial outcomes, and political events have a greater influence on stock markets [2]. Similarly, any economic news on various social media platforms, in either positive or negative terms, can also significantly influence stock markets [3, 4]. Stock market forecasting and analyses of stock returns under different factors have long been a classic but difficult research area, attracting the interest of both economists and computer scientists [5].

The highly volatile nature of the stock market attracts researchers to explore the underlying factors that result in these movements. Moreover, investors must keep track of

the key factors that affect stock returns. Investors need to pay attention to crucial macroeconomic indicators to earn optimal returns on their portfolios. Therefore, stock market prediction is very important for investors and policymakers [6]. In a financially risky marketplace, it is crucial to make very specific predictions about stock returns. Accurate stock prediction leads to market developments, guides investment strategies, and enlightens paths toward optimized stock trading. Stocks are considered one of the most sensitive assets in any economy [7]. Any aggressive variation in the stock market can negatively influence the economy. The main reasons for this risk are market irregularities, uncertainties, and volatility [8, 9]. In this context, stock forecasting tends to be a crucial task because fluctuations in the economy are sometimes quite drastic and sudden, which may lead to a fall in stock markets [10, 11].

More specifically, various complicated economic factors and scenarios affect stock returns. Research indicates many key factors that affect share prices, including interest rates, exchange rates, company performances, political situations, current events, economic conditions, market psychology, natural disasters, and government policies [12–15]. Macroeconomic variables are theoretically considered the main source of stock volatility. Subsequently, these factors are the main indicators of stock returns [16]. These variables make stock prices unstable and challenging to anticipate with high precision. The existing literature includes many approaches suggested by various researchers for stock price prediction tasks. Some research studies have employed historical stock data on various stock markets to make predictions [17]. However, some studies have also employed social media analytics information, such as general sentiment, news, and sentiment regarding specific events [18], to conduct stock market analyses. More precisely, these events include the coronavirus disease 2019 (COVID-19) [19], the British exit from the European Union (Brexit) [20], and the 2019 Nigerian presidential election [21]. In both approaches, the social media-based analysis of big data regarding stocks has gained substantial attention over the past few years [18, 22] because this provides more clarity to investors for improved planning and decision-making. All these stock market prediction-related tasks have been accomplished using several approaches. Whenever any political or unpredictable event happens, it effects the stock market twofold. First, there is a direct effect on the economy because such events become the drivers of future economic and political policies. As a result of this set of policies, macroeconomic indicators fluctuate and affect the stock market [23]. Second, social media reaction to such events accelerates the impact on the stock market through the sentiment triggered by social media. In this context, it is inevitable to investigate the impact of macroeconomic indicators and social media sentiment on stock returns in special circumstances.

Hence, the major research questions are the following: what if stock return analysis is performed using macroeconomic factors by employing the most sophisticated machine learning approaches (i.e., single-layer neural networks)? Second, what is the influence on the accuracy of stock returns if economic uncertainty news sentiment (EUNS) is incorporated alongside macroeconomic factors? Therefore, compared to the existing methods, this study provides a more in-depth stock market analysis given macroeconomic factors and EUNS using single-layer neural networks instead of traditional statistical and regression approaches. Furthermore, the existing studies[2, 24, 25] have analyzed the stock markets of a specific country in terms of macroeconomic factors, whereas this study assesses the stock markets of three well-established countries: Hong Kong, the US, and Turkey. We focus on four key macroeconomic factors, namely, the interest rate, crude oil price, exchange rate, and gold index to check their impact on stock returns for Turkish, Hong Kong, and US companies' stock data. We collected the stock dataset from January 2010 to December 2020 to evaluate the model. We selected the top five performing stocks in these three stock markets based on their trading volume. Furthermore, to investigate the impact of social media sentiment, we constructed an index based on economic uncertainty news on Twitter. We extracted tweets from Twitter regarding certain keywords, namely, "foreign debt," "trade balance," "budget deficit," "exchange rate depreciation," "the law in order," "war on terror," "financial crisis,""political instability," "trade sanctions," "financial sanction," "turmoil period," and "economic downtime." This set of key words establishes an economic uncertainty news sentiment, which is later used as an independent variable to explain stock market returns. Subsequently, a single-layer neural network that is a time-series model is used to investigate the relationship between the exchange rate, interest rate, crude oil price, gold index, the sentiment of economic uncertainty, and stock returns. The contributions of this study are addressed below:

(i) A single-layer neural network is employed to investigate the influence of macroeconomic variables on stock returns, which is quite rare in this context.

(ii) We construct a Twitter sentiment of economic uncertainty news by applying textual analysis using a Twitter dataset.

(iii) We incorporate sentiments related to economic uncertainty news on Twitter into the model to explore their influence on stock returns in the US, Turkey, and Hong Kong.

The remaining sections are arranged as follows: After the introduction, the Related Work section presents the literature review. The third section explains the methodology, and the fourth section reports the results and discussion, followed by the conclusion.

2. Related Work

In this section, we review the task of stock forecasting to examine stock market trends and discuss the literature on studies of the influence of macroeconomic variables on stock returns. This section also emphasizes the many methodologies used in stock market analysis.

2.1. Stock Market Analysis Using Traditional Methods. Examining the literature in terms of stock market analysis or forecasting tasks based on historical data on stock prices, Dash et al. proposed a fine-tuned version of support vector regression by applying grid search techniques to perform stock market predictions [26]. They validated their proposed model on eight different large stock datasets in various domains and attained better performance than existing methods. Similarly, Torres et al. proposed an algorithm based on random trees and the multilayer perceptron (MLP) methods to analyze Apple's stock data [27]. The data employed in this study are also historical, and closing prices are predicted using machine learning algorithms. Ayala et al. [28] suggested several machine learning approaches, including linear regression, support vector regression, artificial neural networks (ANNs), and moving average-based methods. They tested the trading data from three indices which included Ibex35, DAX, and Dow Jones Industrial. Likewise, Mokhtari et al. [29] exploited machine learning approaches for stock market prediction in terms of buying, selling, and holding stocks. They performed both fundamental and technical analyses on the stock, along with feature selection and data-cleaning methods, to improve performance.

2.2. Stock Market Analysis Using Deep Learning Methods. Other than traditional machine learning methods, some researchers have also proposed deep learning-based advanced algorithms in the financial domain of stock data because these techniques perform well in diverse domains [30–32]. For example, Hiransha et al. [33] proposed four kinds of deep neural networks, namely, MLP, recurrent neural networks, long-short-term memory (LSTM) networks, and convolutional neural networks (CNNs) for stock market predictions using historical data. The stock data came from two stock exchanges: the National Stock Exchange of India and the New York Stock Exchange. Nikou et al. conducted a comparative study of machine learning and deep learning approaches for stock market predictions. The data in their study included the closing prices of the iShares MSCI United Kingdom exchange-traded fund. Their analysis observed that deep learning techniques work better than traditional machine learning approaches. Moghar and Hamiche suggested the LSTM model to predict future stock prices [34]. The primary goals of this study were to determine the precision with which a machine learning model can forecast and the number of epochs required to train a model. Sunny et al. [35] proposed a bidirectional LSTM model to predict the stock market. They validated their suggested model on publicly available datasets of stocks.

2.3. Stock Market Analysis with Sentiment Data. In contrast to the above-mentioned studies, some researchers have exploited the data based on sentiments to examine their influence on stock market predictions. For instance, Li et al. [36] incorporated stock prices and sentiments to perform stock predictions. Both sources of information were input into an LSTM model separately to estimate the stock return values. Jin et al. [10] involved investor sentiments in predicting stock prices by employing an attention-based LSTM model that focuses on more meaningful information. Furthermore, using empirical modal decomposition, they progressively deconstructed a complicated series of stock prices. Moreover, their results demonstrated that investors' emotional tendencies are useful for improving expected outcomes. Additionally, the influence of certain mega-events, such as the COVID-19 pandemic, on various stock markets has also been analyzed. For instance, Lee [19] exploited the influence of COVID-19 on US stock markets. This study investigated whether the Daily News Sentiment Index forecasted US industrial returns differently by designing a regression model in which the dependent variable was the industry's excess returns.

Gupta et al. [37] also suggested fusing historical data with sentiment data to accurately forecast the future of financial stocks. The model they designed is an LSTM model that best models the trends of future stock prices. The latest studies have also employed optimization-based methods combined with deep learning models to acquire more optimized values for stock prices during forecasting. For instance, Chung and Shin optimized architectural elements of the LSTM model, such as window size, with a genetic algorithm (GA) [38] because these structural elements play an important role in improving the performance of LSTM and ultimately significantly influence forecasting of stock prices. This study aimed to analyze the temporal characteristics of stock market data by proposing a structured technique for determining the time window size and architecture for the LSTM model. Similarly, Chung and Shin optimized the model topology using a GA; however, the underlying model was a CNN [39]. Their study indicated that a hybrid of CNN and GA outperformed the existing stock market prediction methods. Zhang et al. proposed a novel algorithm with the most advanced approach (i.e., generative adversarial networks with MLP as the discriminator model) that incorporates an LSTM model as a generator to predict stock prices [40]. The aim of the generator model built using LSTM was to extract the stock data distributions from the supplied stock data and then produce the same data, whereas the discriminator aims to differentiate between actual and generated stock data. Moreover, the latest research into stock trading and forecasting strategies exploits the application of deep reinforcement learning algorithms [41].

2.4. Analysis of Stock Returns with the Influence of Macroeconomic Variables. The mentioned studies conducted stock forecasting-related tasks using historical data, such as the open price of a stock and its high and low prices. However, these indicators are very basic because the stock market is quite sensitive and exposed to macroeconomic factors (e.g., the exchange rate, oil price, interest rate, and gold price) [42]. The effect of macroeconomic variables on the stock market is highly linear. The exchange rate of the stock market has a positive correlation with these external or macroeconomic variables, but this can vary between different markets and periods. Any general changes, such as

foreign investment restrictions, induce changes to the stock market. Therefore, investigating the relationship between the stock exchange and macroeconomic variables is important [43]. In this respect, several pieces of research have been conducted to address the relationship between macroeconomic variables and stock market returns. Some have found a relationship between macroeconomic variables in the stock market, such as the real gross domestic product, aggregate price level, exchange rate, money supply, interest rate, and production index [44]. The interest rate, inflation, and money supply have a bidirectional relationship with stock returns [45]. News sentiments are also a significant variable when estimating stock market returns [46].

Moreover, contradictory results are reported in the existing literature regarding the relationship between these variables. The relationship is quite dynamic and varies between countries [47]. Specifically, in the context of macroeconomic factors, Celebi and Hönig analyzed the German stock index in terms of the influence of macroeconomic factors [2]. They used data covering 27 years, and the results reported in this work indicate that many macroeconomic factors had a major influence on stock returns during pre-crisis and post-crisis times. Similarly, Omodero and Mlanga analyzed macroeconomic variables in Nigeria's stock markets using the regression method [48]. Their investigation revealed that the exchange and interest rates have no substantial influence on the share price index. However, the inflation rate has a considerable detrimental influence on the share price index. Likewise, Ndlovu et al. [25] and J. Khan and I. Khan [24] worked on the stock exchanges of Johannesburg and Karachi to study the influence of macroeconomic variables. These studies involved several statistical analysis techniques and tests, such as the autoregressive distributed lag model, to examine the influence. Khan et al. observed that the money supply, exchange rate, and interest rate are essential macroeconomic variables that affect stock returns. In recent times, neural network models to investigate the relationship between macroeconomic variables and stock returns have been quite rare. Therefore, this study uses this model to empirically investigate the relationship between the gold index, crude oil price, interest rate, exchange rate, EUNS, and stock market returns.

3. Materials and Methods

This section elaborates on the dataset in this study and discusses the methodological steps to conduct the study. We describe the data collection procedure for analysis in the first stage and provide a step-by-step explanation to illustrate how the acquired data are used to study the influence of macroeconomic variables and EUNS on stock market returns for three nations. Figure 1 depicts a representation of the methodology.

3.1. Data Collection. To assess the performance of the proposed model on historical stock data for technical analysis, we take daily data from the top five performing stocks in the Standard and Poor's 500, the Hong Kong stock exchange, and the Borsa Istanbul stock exchange, as listed in Table 1. Similarly, the currency rate, interest rate, gold price, and crude oil price are all considered to be macroeconomic variables. The data were acquired from January 2010 to December 2020. Subsequently, for the fundamental analysis, we employ sentiment analysis on tweets indexed against several keywords, including "foreign debt," "trade balance," "budget deficit," "exchange rate depreciation," "the law in order," "war on terror financial crisis," "political instability," "trade sanctions," "financial sanctions," "turmoil period," and "economic downtime."

3.2. Proposed Model for Technical and Fundamental Analyses of Stock and Sentiment Data with Macroeconomic Variables. After data acquisition, a model based on deep neural networks was designed to perform regression and estimate the coefficient values for macroeconomic variables and EUNS. Equations (1) and (2) compute the values of the coefficients.

$$R_\tau = \gamma 0 - \gamma 1\left(G_i\right) - \gamma 2 * \left(C_0\right) - \gamma 3\left(I_r\right) - \gamma 4\left(E_x\right), \tag{1}$$

$$R_\tau = \gamma 0 + \gamma 1\left(G_i\right) + \gamma 2\left(C_o\right) + \gamma 3\left(I_r\right) + \gamma 4\left(E_x\right) + \gamma 5\,(\mathrm{S}). \tag{2}$$

In the above equations, G_i, C_o, I_r, E_x, and S represent the gold price index, crude oil price, daily interest rate, exchange rate, and EUNS, respectively. Specifically, the neural network technique is used for the linear regression problem.

Generally, linear regression refers to the set of problems in which we want to model the relationship between dependent and independent variables. This method is one of the most popular supervised machine learning algorithms in which the projected output is continuous and the slope indicates constant learning. Linear regression is classified into simple and multiple linear regression. Simple linear regression has only one independent variable and a bias term. However, multiple linear regression must have more than one independent variable. These regression problems can be formulated with the most sophisticated machine learning algorithms (i.e., ANNs). Also known as connectionist systems, these ANNs are inspired by the structure of the human brain and are very efficient approaches for designing predictive or regression models. These neural networks enable several machine learning algorithms to coordinate and handle complex inputs. Due to these characteristics, an algorithm can accomplish tasks, and the underlying algorithm is not usually designed with any task-specific rules. For instance, in computer vision, the system can perform image recognition and object detection in different domains [49, 50]. However, these tasks use the most advanced variants of ANNs (i.e., CNNs and object-detection models).

In fact, ANNs are a strong tool for determining the association between input and output variables, which can be accomplished by training the ANNs on a large set of training records containing input and output data. Generally, the ANN architecture consists of units or nodes with

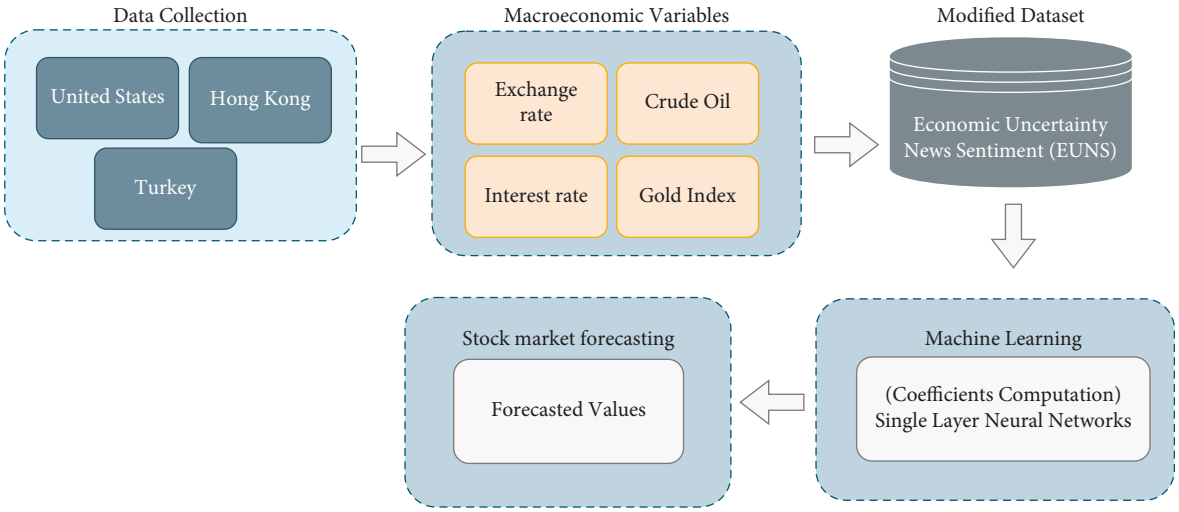

Figure 1: Overview of the proposed methodology.

Table 1: Set of countries and companies in the analysis.

	Countries		
Top companies	United Nations	Turkey	Hong Kong
	Apple	AK Bank	China Merchant Bank
	Citi Group	Arcelik	Industrial and Commercial Bank
	General Electric	Dogus	Ping Insurance Co
	Microsoft	KOC Holdings	HK Index
	Google	Vestel	
	US Index	Turkey Index	

weighted connections between them, where each unit introduces and conveys certain information to the network. This method works by first taking a vector of inputs, such as $X = (x_1, x_2, x_3, \ldots, x_n)$, and generating a predictive model with the help of a mathematical function. In the next stage, the ANN starts learning by fine-tuning the weights present on connections between neurons, followed by measuring the model error, which is the difference between the projected model output and the actual values. This process is repeated many times or for a set number of epochs until it finds a model with an error near zero. Using ANNs, we can model any real-world problem because they are self-adaptive. They can be single-layer or multi-layer neural networks. We employed a single-layer network with only one input and one output layer to model the regression problem. A model is designed to take inputs of independent variables as a set and learn to find the best weights such that the value of the dependent variable and model outputs are nearly equal. In this case, these independent variables are macroeconomic variables' sentiment values. We consider the following simple linear regression function, given in the following equation:

$$y = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3, \ldots, w_n x_n. \tag{3}$$

In the above equation, x_1, x_2, x_3, and x_n are independent variables or features in a given input vector. In addition, w_1, w_2, w_3, and w_n are the coefficients and weights of the predictive model, and w_0 is the bias term. The proposed architecture is divided into one input and one output layer. The number of units in the input layer equals the total number of independent variables, and the output layer has one unit. There are direct connections between every input and the output units and associated weights. The neural network optimizes these weights throughout every iteration using the Adam optimizer. This algorithm calculates the individual learning rates for different parameters. Moreover, to adapt the learning rates, the first and second moments of the gradient are also calculated for each coefficient or weight of the model. The expected value of the random variable is defined as its moment, as indicated in equation:

$$m = E[X^n]. \tag{4}$$

This random variable is used to represent the loss function of the neural network. Furthermore, after one iteration finishes, the weights or coefficients of the linear regression model are updated using the weight update equation described in equation (5) for all weights (i.e., w_0, w_1, w_2, w_3, and w_n).

$$W_n = W_{n-1} - \eta \frac{\widehat{m}_t}{\sqrt{\widehat{v}t} + \varepsilon}, \tag{5}$$

where W_{n-1} is the value of the old weight, η is the step size, and the values of $\widehat{m}_t$ and $\widehat{v}t$, which represent the moments

and variance, are calculated by equations (6) and (7), respectively.

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t}, \tag{6}$$

$$\widehat{v}_t = \frac{v_t}{1-\beta_2^t}, \tag{7}$$

where β_1 and β_2 are the hyperparameters in equations (6) and (7), and equations (8) and (9) are used to calculate m_t and v_t.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\, g_t, \tag{8}$$

$$v_t = \beta_2 m_{t-2} + (1-\beta_2) g_t^2. \tag{9}$$

The first moment is the mean m_t, and the second moment is the variance v_t. Furthermore, when the model converges and determines the best coefficients after updating the weights individually in every iteration, after the last iteration, the weights or coefficients are extracted and stored. The optimized loss function is the mean squared error function, defined as follows:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2. \tag{10}$$

In equation (10), N denotes the total number of instances in stock data, Y_i is the actual value of the dependent variable, and $\widehat{Y}_i$ represents the predicted value of the dependent variable. In the following stage, for each unobserved data point, we load the stored coefficients and multiply them by the relevant dependent variables to obtain the required value of the dependent variable. Figure 2 depicts the proposed model.

4. Results and Discussion

This section presents the results for all three selected countries (i.e., the US, Turkey, and Hong Kong) and a theoretical discussion. Subsequently, we compared existing studies regarding macroeconomic variable analysis with stock returns.

4.1. Analysis of Descriptive Statistics for Different Countries. Table 2 lists the descriptive statistics for all macroeconomic variables for the US. The columns in Table 2 indicate all macroeconomic variables, and the rows display the mean, median, standard deviation, Jarque-Bera value, and a number of observations. Table 2 indicates how the Jarque-Bera test reveals that all variables follow non-normal distributions. The exchange rate has a very large Jarque-Bera test value for all variables. However, the mean values are 2.258, 0.582, 1.209, 69.321, and 17.365 for the index return, interest rate, exchange rate, crude oil price, and gold price, respectively. Moreover, the total number of observations for all variables is 2,750. In addition, the median values of the variables are 2.102, 0.463, 1.025, 56.321, and 15.963, and the standard deviation values are 0.0258, 0.862, 0.014, 0.254, and 0.372, in that order. The gold price index has greater fluctuations because its standard deviation is the highest of all variables.

Table 3 lists the descriptive statistics of variables for Turkey. Like the descriptive statistics for the US, the Jarque-Bera test demonstrates that all the variables follow a non-normal distribution. For the index return, interest rate, and exchange rate, the mean values are 1.258, 1.225, and 0.968; the standard deviations are 0.368, 0.124, and 0.0124; and the median values are 0.968, 1.102, and 0.752, respectively. The Jarque-Bera test result is greater for interest rates but lower for index returns.

Last, Table 4 presents the descriptive statistics of variables, including the interest rate and exchange rate for Hong Kong. The Jarque-Bera test reveals that all these variables have a non-normal distribution. The exchange rate has the greatest Jarque-Bera value, and the index rate has the lowest. For the index return, interest rate, and exchange rate, the mean values are 2.368, 0.385, and 2.582. In addition, the standard deviation values are lower for all variables, including the index return, interest rate, and exchange rate, which indicate fewer fluctuations in the overall observations.

4.2. Results with the Augmented Dickey-Fuller Unit Rate Test. If the number of observations is compared with the previous two nations, the overall number of observations for Hong Kong is greater than that for the US and Turkey. Generally, non-stationarity is a prevalent issue with time-series data. More explicitly, when the mean and standard deviation are time-dependent, it causes a "unit root problem." The augmented Dickey-Fuller (ADF) test analyzes the unit root problem. The ADF test investigates the unit root hypothesis against the alternative of no unit root. When the problem of unit root exists, the data are considered nonstationary, causing bias in the estimated parameters. Table 5 provides the results of the ADF test.

The results indicate that most stock return data and exchange rates are stationary at the first level, whereas the interest rate, crude oil price, and gold index are stationary at the first difference. In Table 5, the first column lists the variables. The second and third columns present the values of the ADF test with the first differences, whereas the last column displays the critical values at 5%. These values were computed for each country and their respective stock returns. Table 5 demonstrates that the critical values for all countries remain the same at −2.86. The ADF test (first difference) in the US for the crude oil price was −7.369 and for the gold price index was −12.367. Similarly, the value of the ADF test (the first difference between the interest and exchange rates) was −4.558 and −3.664 for Turkey; however, it was −4.360 and −9.361 for Hong Kong. The ADF test (first difference) for the exchange rate for Hong Kong was less than that of Turkey.

The ADF test (at level) was also computed for each country and their respective stock returns. The macroeconomic variables of the exchange and interest rates for the US have ADF test (at level) values of about −2.946 and −1.368, respectively. Likewise, these respective values are −0.369 and −1.962 for Turkey and −1.367 and −2.301 for Hong Kong.

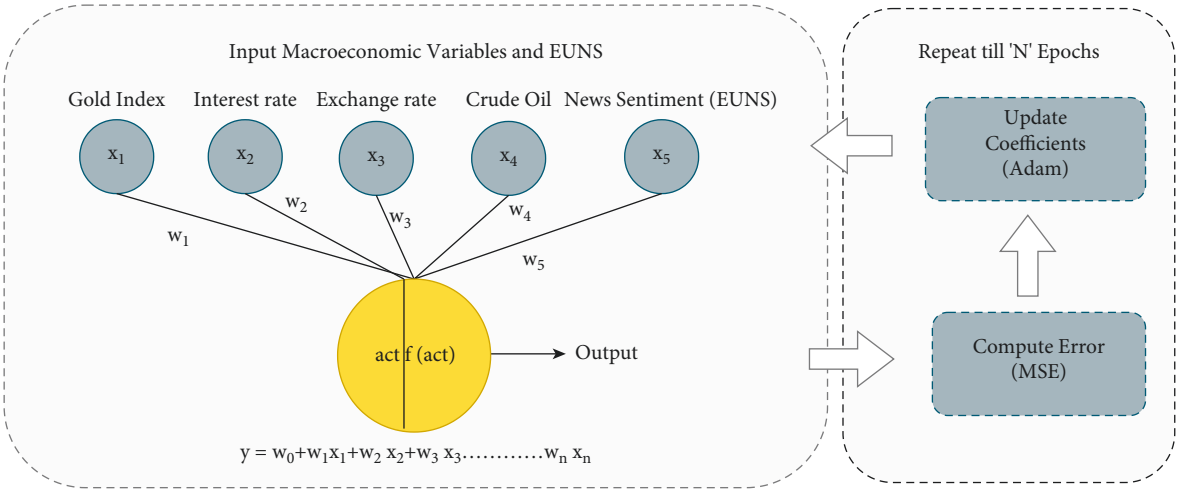

Figure 2: Computation of coefficients for macroeconomic variables.

Table 2: Descriptive statistics for the United States.

Variables	Index return	Interest rate	Exchange rate	Crude oil price	Gold price index
Mean	2.258	0.582	1.209	69.321	17.365
Median	2.102	0.463	1.025	56.321	15.963
SD	0.026	0.862	0.014	0.254	0.372
Jarque-Bera	68.225***	15.230***	85043.660***	36.925***	25.221***
Observations	2750	2750	2750	2750	2750

****denotes significance at 1% level.

Table 3: Descriptive statistics for Turkey.

Variables	Index return	Interest rate	Exchange rate
Mean	1.258	1.225	0.968
Median	0.968	1.102	0.752
SD	0.368	0.124	0.012
Jarque-Bera	20.258***	39.639***	24.223***
Observations	2780	2780	2780

***denotes significance at 1% level.

Table 4: Descriptive statistics for Hong Kong.

Variables	Index return	Interest rate	Exchange rate
Mean	2.368	0.385	2.582
Median	1.960	0.225	2.301
SD	0.012	0.047	0.029
Jarque-Bera	22.369***	36.441***	890.228***
Observations	2800	2800	2800

***denotes significance at 1% level.

Thus, this ADF test appropriately demonstrates the proper stationarity of time-series data for these nations.

4.3. Regression Results and Computation of Coefficients. To compute the regression results and calculate the coefficients, we used (1) to investigate the influence of macroeconomic variables, including the gold index ($\mathbf{G_i}$), crude oil price ($\mathbf{C_o}$), interest rate ($\mathbf{I_r}$), and exchange rate ($\mathbf{E_x}$). Similarly, equation (2) investigates the influence of economic news (S) sentiment on stock returns for all countries. In the first stage, the influence of the gold index, crude oil price, interest rate, and the exchange rate was analyzed on the stock returns of the US stock market without involving the sentiment of the economic news (*S*). For this purpose, we used the stock returns of the top five performing companies along with the Standard and Poor's 500 index. Table 6 lists the results for each country.

Each column in Table 6 provides the coefficient value for each macroeconomic variable. Moreover, the rows indicate

Table 5: Unit rate test of different countries.

	Variables	ADF test (at level)	ADF test (at 1st difference)	Critical values at 5%
Countries	Crude oil price	−1.589	−7.369***	−2.86
	Gold price index	−2.458	−12.367***	−2.86
US Stock Return	Apple	−72.045***		−2.86
	Citi Group	−34.968***		−2.86
	General Electric	−60.127***		−2.86
	Microsoft	−72.840***		−2.86
	Google	−58.635***		−2.86
	US Index Returns	−52.360***		−2.86
The US	Interest rate	−1.368	−7.888***	−2.86
	Exchange rate	−2.946		−2.86
Turkey Stock Return	AK Bank	−2.369	−5.697***	−2.86
	Arcelik	−3.895***		−2.86
	Dogus	−12.360***		−2.86
	KOC Holdings	−24.610***		−2.86
	Vestel	−6.323***		−2.86
	Turkey Index	−8.336***		−2.86
Turkey	Interest rate	−0.369***	−4.558***	−2.86
	Exchange rate	−1.962	−3.664***	−2.86
Hong Kong Stock Return	China Merchant Bank	−3.568***		−2.86
	Industrial and Commercial Bank	−2.880**		−2.86
	Ping Insurance Co	−12.336***		−2.86
	HK Index	−7.813***		−2.86
Hong Kong	Interest rate	−1.367	−4.360***	−2.86
	Exchange rate	−2.301	−9.361***	−2.86

***and **denote significance at the 1% and 5% levels, respectively; ADF: augmented Dickey-Fuller.

Table 6: Coefficient outputs for the US without sentiment.

		Parameters				
	Companies	γ_0	γ_1	γ_2	γ_3	γ_4
SLP	Apple	0.0011	−0.1133** (−2.6342)	−0.1980 (−1.2358)	−0.1194*** (−3.5632)	−0.2146 * (−1.7523)
	Citi Group	0.1487	−0.0208** (−1.9730)	−0.0044 (−1.0260)	−0.0423*** (−4.5320)	−0.4389** (−2.3255)
	General Electric	−0.0025	−0.0893*** (−3.6981)	−0.1387* (−1.7283)	−0.0713** (−2.0861)	−0.1269*** (−7.0036)
	Microsoft	−0.0000	−0.1417*** (−12.5853)	−0.0793 (−0.5581)	−0.0931*** (−3.2260)	−0.0749** (−1.9931)
	Google	−0.0009	−0.1962*** (−8.9680)	−0.0217** (−2.0025)	−0.1492*** (−2.6089)	−0.0034*** (−2.7763)
	US Index	0.0007	−0.0995*** (−10.8875)	−0.1643** (−2.6987)	−0.0804*** (−3.8910)	−0.1529*** (−3.1250)
OLS	Apple	0.0032	−0.0251 (−1.2365)	−0.2153 (−0.9630)	−0.1023** (−2.6980)	−0.0126* (−1.6420)
	Citi Group	0.1692	−0.3654 (−1.3623)	−0.0321 (−0.6980)	−0.0214** (−2.3610)	−0.3647 (−1.2045)
	General Electric	−0.0030	−0.0896*** (−3.1250)	−0.0032* (−1.6402)	−0.0631 (−1.2561)	−0.0378** (−2.1253)
	Microsoft	−0.0003	−0.1023** (−2.0021)	−0.0032 (−1.236)	−0.3680 (−1.2365)	−0.2256 (−0.0023)
	Google	−0.0036	−0.1062** (−2.0125)	−0.0361** (−2.5540)	−0.3690** (−2.3600)	−0.3265* (−1.6430)
	US Index	0.0362	−1.2632 (−6.5243)	−0.3620 (−1.3620)	−0.5326** (−2.3687)	−0.2569** (−1.9682)

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

the top five performing companies' stock returns. For instance, in the case of the SLP (single-layer perceptron model), the coefficients of macroeconomic variables for Apple Company are 0.0011, −0.1133, −0.1980, −0.1194, and −0.2146. Similarly, Table 6 provides the values of coefficients for other companies also. The findings suggest that the influence of the gold index, oil price, interest rate, and exchange rate is highly significant and negative. As a result, any positive shock in the exchange rate causes stock returns to rise. Similarly, an increase in the gold index causes the stock return to decrease because the gold index is a relatively less risky option for investors. These results align with the existing literature (e.g., [51–54]). Subsequently, we employ equation (2) to investigate the influence of the gold index, crude oil price, interest rate, exchange rate, and sentiment of economic news on stock returns in the US stock market. For comparative analysis, we also report results of estimated coefficients based on OLS (Ordinary least square). All the coefficients are mostly negative and significant. However, the SLP model outperforms the OLS because most of the coefficients are highly significant, unlike the OLS.

Table 7 presents the results that include sentiment as another variable. Like Table 6, the columns indicate the coefficient values, including the coefficient of sentiment, and the rows indicate the companies. For instance, the first row

Table 7: Coefficient outputs for the US with sentiment.

	Companies	Parameters					
		γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
SLP	Apple	−0.0003	−0.1164* (−1.6842)	−0.2797** (−2.2201)	−0.0737*** (−3.6128)	−0.2751** (−2.6681)	−0.0391*** (−8.6680)
	Citi Group	−0.4559	−0.0178** (−2.0973)	−0.0035 (−1.0260)	−0.1832** (−2.5320)	−0.1885 (−1.3255)	−0.0654*** (−3.225)
	General Electric	0.00501	−0.0036 (−0.7123)	−0.0521* (−1.8283)	−0.0101** (−2.0861)	−0.0335*** (−7.0036)	−0.1026** (−10.5638)
	Microsoft	0.0089	−0.0020*** (−12.5853)	−0.1756 (−0.5581)	−0.0646*** (−3.2260)	−0.2097** (−1.9931)	−0.0068** (−2.8969)
	Google	0.0029	−0.0116* (−1.9080)	−0.0968 (−1.0025)	−0.0019*** (−3.6157)	−0.09032** (−2.0563)	−0.0769*** (−5.8801)
	US Index	−0.0007	−0.0550* (−1.7675)	−0.2368* (−1.6987)	−0.0142*** (−3.8910)	−0.2369** (−2.1250)	−0.1199** (−2.3601)
OLS	Apple	−0.0023	−0.0012** (−2.0360)	−0.1578* (−1.6890)	−0.0589*** (−3.5580)	−0.2875** (−2.3690)	−0.6890*** (−6.3281)
	Citi Group	−0.0036	−0.3482* (−1.6480)	−0.1258 (−0.3670)	−0.3470** (−2.3600)	−0.1244 (−0.7820)	−0.0224* (−1.8950)
	General Electric	0.3600	−0.0125 (−0.0367)	−0.0362* (−1.6432)	−0.0125* (−1.6980)	0.7785*** (3.6650)	−0.4457*** (−6.3325)
	Microsoft	0.0025	−0.0480** (−7.6380)	−0.7412 (−0.4450)	−0.0889** −(2.2236)	−0.2287 (−0.3668)	−0.0560 (−1.3580)
	Google	0.0235	−0.2258 (−1.4480)	−0.0036 (−0.4412)	−0.4521 (−1.0231)	−0.4425** (−1.9632)	−0.0125*** (−3.1425)
	US Index	−0.0034	−0.0142 (−1.2365)	−0.0147 (−1.5243)	−0.1252* (−1.7630)	−0.1425** (−2.5630)	−0.2250**(−2.1125)

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

provides the values of coefficients for Apple (i.e., −0.0003, −0.1164, −0.2797, 0.0737, −0.2751, and −0.0391).

Likewise, the subsequent rows provide the coefficient values for the remaining companies under US stock returns. The findings suggest that the gold index, interest rate, and exchange rate have highly significant and negative influences. All the coefficients of these variables are negatively significant at the 1% level, and any positive shock in the exchange rate causes the stock returns to increase. The coefficient of social media sentiment toward economic news is highly significant and negative at the 5% and 1% significance levels. The statistical significance of the EUNS indicates that during the period of a fiscal budget announcement, any economic uncertainty news negatively influences stock returns. For comparative analysis, we also report results of estimated coefficients based on OLS (ordinary least square). All the coefficients are mostly negative and significant. However, the SLP model outperforms the OLS because most of the coefficients are highly significant, unlike the OLS.

In the second experiment, we assessed the values of coefficients for Turkey with two experimental settings. In the first setting, we used (1) to investigate the influence of the gold index, crude oil price, interest rate, and exchange rate on stock returns in the Turkish stock market without including sentiment as a variable. We used the stock returns of the top five performing firms and the BIST 100 index. Table 8 presents the findings. The columns in Table 8 indicate the coefficients, and the rows indicate the selected firms.

These firms are AK Bank, Arcelik, Dogus, KOC Holdings, Vestel, and Turkey Index. More explicitly, the values of coefficients for AK Bank are −0.7458, 0.0015, −0.0045, 0.0003, −0.0013, and −0.0017. Similarly, for Arcelik, the values of coefficients are 0.0015, −0.0818, 0.0595, −0.0194, and 0.1275. Subsequently, the remaining rows of Table 8 present the values of coefficients for the remaining top five firms in Turkey. According to the results, the coefficients for the interest and exchange rates are extremely significant and negative. Any positive shock in the exchange rate leads to increased stock returns. Similarly, an increase in the interest rate causes stock returns to decrease. However, the crude oil price and gold index are insignificant. These findings are similar to the results reported by Toparlı et al. [55] in the context of Turkey using the time-varying parameter vector autoregressive approach. For comparative analysis, we also report results of estimated coefficients based on OLS (Ordinary least square). All the coefficients are mostly negative and significant. However, the SLP model outperforms the OLS because most of the coefficients are highly significant, unlike the OLS.

In the second experimental setting, we used equation (2) to investigate the influence of the gold index, crude oil price, interest rate, exchange rate, and the additional variable of the sentiment of economic news on stock returns for the Turkish stock market. Table 9 displays the results for this experimental setting. The columns in Table 9 indicate the coefficients from γ° to $\gamma 5$, including the sentiment variable. The rows list the values of the top five firms in Turkey, as given in the previous experimental setting. Our findings suggest that the gold index, interest rate, and exchange rate have highly significant and negative influences. All the coefficients of these variables are

Table 8: Coefficients outputs for Turkey without sentiment.

	Companies	Parameters				
		γ_0	γ_1	γ_2	γ_3	γ_4
SLP	AK Bank	−0.7458	−0.1942* (−1.8251)	0.0308 (0.3680)	−0.0794** (−2.6687)	−0.0104*** (−3.6897)
	Arcelik	0.0015	−0.0818 (−1.0021)	0.0595* (0.2421)	−0.0194*** (−3.2258)	−0.1275*** (−6.3360)
	Dogus	−0.0045	−0.0053 (−1.2253)	−0.0081 (−0.0225)	−0.0042** (−2.021)	0.0085*** (−5.4420)
	KOC Holdings	0.0003	−0.0586 (−1.5581)	0.0790 (1.0258)	−0.1313** (−1.9980)	−0.0181* (−1.8412)
	Vestel	−0.0013	−0.0672 (−1.3760)	−0.0659 (−0.9985)	−0.0202*** (−6.2213)	−0.1177*** (−8.6601)
	Turkey Index	−0.0017	−0.0668 (−0.8962)	0.1446 (0.0258)	−0.1187** (−2.6621)	−0.0128** (−2.0170)
OLS	AK Bank	−0.2563	−0.0124 (−1.6347)	0.5692** (2.3610)	0.0365 (1.3481)	−1.3650** (−2.5560)
	Arcelik	0.0012	−1.4458 (−1.5520)	0.0523 (0.0030)	−0.0365* (−1.8963)	−1.2480** (−2.4120)
	Dogus	−0.2570	−0.0124 (−0.2250)	−0.1240 (−0.7890)	−0.1022 (−1.3580)	−0.3658*** (−3.6558)
	KOC Holdings	0.0014	−0.0124 (−1.3560)	0.0124 (1.3610)	−0.1245* (−1.8860)	−0.0115 (−1.5520)
	Vestel	0.0036	−0.0023 (−0.1258)	−0.2568 (−0.3480)	−0.2540 (−0.4580)	−0.1024** (−2.5580)
	Turkey Index	0.3152	−0.0558 (−0.4280)	1.4580* (1.8320)	−0.0530* (−1.9680)	−0.9630** (−2.4520)

***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 9: Coefficient outputs for Turkey with sentiment.

	Companies	Parameters					
		γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
SLP	AK Bank	−0.5609	−0.0328 (−1.3694)	−0.0448 (−0.3325)	−0.0016** (−2.5821)	−0.0123*** (−5.3368)	−0.4417*** (−7.3621)
	Arcelik	0.0009	−0.0123** (−2.3324)	0.0001 (1.0025)	−0.0068** (−2.3369)	−0.0037*** (−7.9980)	−0.1147** (−2.0178)
	Dogus	−0.0053	−0.0094*** (−3.6687)	−0.0142 (−0.2258)	−0.0020*** (−3.1201)	−0.0082*** (−2.9836)	−0.0081*** (−3.6612)
	KOC Holdings	−0.0025	−0.0186*** (−4.6674)	−0.0031 (−1.6237)	−0.0102** (−1.9932)	−0.0023*** (−12.3546)	−0.1057*** (−8.3691)
	Vestel	0.0034	−0.0150*** (−12.9986)	−0.0027 (−0.0089)	−0.0088* (−1.6794)	−0.0071*** (−3.2257)	−0.0947** (−2.6389)
	Turkey Index	−0.0028	−0.0393*** (−16.2258)	0.0066 (1.0028)	−0.0226*** (−3.2292)	−0.0068* (−4.5528)	−0.1636*** (−3.2630)
OLS	AK Bank	−0.5630	−0.5230 (−1.4030)	−0.4236 (−0.8632)	−1.7410* (−1.8820)	−0.1423*** (−3.7430)	−0.4620*** (−6.9930)
	Arcelik	0.0742	−0.4620* (−1.9630)	−0.1456 (−0.4310)	−0.1036** (−2.2310)	−0.4250*** (−4.8632)	−0.4520* (−1.8850)
	Dogus	0.0042	−0.0467** (−2.4520)	−0.4460 (−0.3336)	−0.0325** (−1.996)	−0.3460 (−1.4630)	−0.2200 (−1.3870)
	KOC Holdings	0.3360	−0.7630*** (−3.6690)	−0.3340 (−0.6980)	−0.0111 (−1.4520)	−0.0021*** (−7.6460)	−0.0364*** (−3.6540)
	Vestel	0.4560	−0.7520 (−1.6280)	−0.0240 (−0.4420)	−0.3360 (−1.3120)	−0.1270** (−2.4630)	−0.1860 (−1.4850)
	Turkey Index	−0.1120	−0.0125*** (−6.2240)	0.0460 (0.4430)	−0.3640** (−2.1360)	0.0125** (−2.3120)	−0.1240 (1.4560)

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

negatively significant at the 1% level. An increase in the price of the gold index becomes attractive for investors, which negatively influences stock returns. Any positive shock in the exchange rate causes the stocks' returns to increase. The coefficient of EUNS is highly significant and negative, indicating that any economic uncertainty news negatively influences stock returns during the period leading up to the fiscal budget release. For comparative analysis, we also report results of estimated coefficients based on OLS (ordinary least square). All the coefficients are mostly negative and significant. However, the SLP model outperforms the OLS because most of the coefficients are highly significant, unlike the OLS.

In the last experiment, we estimated the values of coefficients for Hong Kong. This experiment was also divided into two scenarios. In the first, we used (1) to investigate the influence of the gold index, crude oil price, interest rate, and exchange rate on stock returns in the Hong Kong stock market without involving the sentiment variable. To accomplish this, we used the stock returns of the top five performing companies alongside the Hong Kong stock exchange index. Table 10 presents the results of this experimental scenario.

The columns in Table 10 display the values of the coefficients, and the rows indicate the top three companies in

Table 10: Coefficient outputs for Hong Kong without sentiment.

	Companies	Parameters				
		γ_0	γ_1	γ_2	γ_3	γ_4
SLP	China Merchant Bank	−0.2290	−0.1439 (−0.2548)	−0.0030** (−2.0145)	−0.0259** (−2.3684)	−0.2028*** (−3.0125)
	Industrial and Commercial Bank	0.6643	−0.4067 (−1.3582)	−0.0082** (−2.8560)	−0.0736** (−1.9984)	−0.5098** (−2.1584)
	Ping Insurance co	−0.6343	−0.2024* (−1.7837)	−0.0023** (−2.3689)	−0.0268*** (−3.2514)	−0.2131*** (−3.5562)
	HK Index	−0.0008	−0.1593* (−1.8920)	−0.1876** (−2.0258)	−0.0792* (−2.5218)	−0.1759** (−1.9725)
OLS	China Merchant Bank	−0.0210	−0.2350 (−0.4610)	−0.0412 (−1.6310)	−0.0145* (−1.7820)	−0.1048** (−2.1050)
	Industrial and Commercial Bank	0.4420	−0.0230 (−0.2250)	0.1205* (−1.6630)	−0.3660 (−0.8960)	0.5520 (1.4420)
	Ping Insurance Co.	−0.3360	−0.1020 (−1.0020)	−0.1254** (−1.9980)	−0.3360** (−2.2630)	−0.3360* (−1.8820)
	HK Index	0.2250	−0.2236 (−1.3650)	−0.3360* (−1.6630)	−0.4450** (−2.2540)	−0.4420* (−1.6880)

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Hong Kong: China Merchant Bank, Industrial Commercial Bank, Ping Insurance Co., and HK Index. Table 9 indicates that the coefficient values of the China Merchant Bank are −0.229, −0.1439, −0.0030, −0.0259, and −0.2028. Likewise, the coefficient values of the Industrial and Commercial banks are −0.229, −0.1439, −0.0030, −0.0259, and −0.2028. Likewise, the coefficient values of the Industrial and Commercial banks are −0.6643, −0.4067, −0.0082, −0.0736, and −0.5098. These findings suggest that the crude oil price, interest rate, and exchange rate are highly significant and negatively influenced. All coefficients of these variables are negatively significant at either the 5% or 1% significance levels. Any positive shock in the exchange rate causes the stocks' returns to increase. These results are similar to those of Khan et al. [56], who reported that the oil price negatively influences stock returns in the short and long run. For comparative analysis, we also report results of estimated coefficients based on OLS (ordinary least square). All the coefficients are mostly negative and significant. However, the SLP model outperforms the OLS because most of the coefficients are highly significant, unlike the OLS.

In the next scenario, we employ equation (2) to investigate the influence of the gold index, crude oil price, interest rate, and exchange rate by including the sentiment of economic news on stock returns in the Hong Kong stock market. Table 11 provides the results of this scenario for Hong Kong.

The effects of the gold index, interest rate, and exchange rate are highly significant and negative. All the coefficients of these variables are negatively significant at the 1% level. Any positive shock in the exchange rate increases the stock returns. The coefficient of social media sentiment toward economic news is highly significant and negative. Thus, during the period of a fiscal budget announcement, any economic uncertainty news negatively affects stock returns. For comparative analysis, we also report results of estimated coefficients based on OLS (ordinary least square). All the coefficients are mostly negative and significant. However, the SLP model outperforms the OLS because most of the coefficients are highly significant, unlike the OLS.

4.4. Results of Predictions with Macroeconomic Factors and without Sentiment. In this section, we analyze the performance of the proposed model in terms of predicting the returns of different companies in the US, Turkey, and Hong Kong. In the first step, we tested the models using macroeconomic factors without including sentiment. We trained the single-layer perceptron model using macroeconomic variables such as the exchange rate, interest rate, gold index, and oil price across 50 epochs. In regression, these variables are regarded as dependent variables, whereas the target variable is the returns of various companies.

The parameters of a single-layer perceptron include the weight optimizer, which is Adam; the loss function is "Mean Squared Error," and the batch size is 4. The input layer of a single-layer neural network consists of units equal to dependent variables, while the last consists of one unit (neuron) representing the output value. Figure 3 depicts the MSE loss during single-layer neural network training for enterprises from all nations. The first graph illustrates the training loss on the data of all Hong Kong companies, whereas the second graph depicts loss curves on US companies, and the third graph depicts curves on Turkish companies. The graphs show that a single-layer neural network converges quite smoothly and with near-zero error.

In addition, we have computed the values of RMSE (root mean square error), MAE (mean absolute error), and MSE (mean squared error) to evaluate the robustness or performance of single-layer perceptrons and the OLS method. Table 12 shows the values of RMSE, MSE, and MAE for companies in Hong Kong, the US, and Turkey with single-layer perceptron. Each part of Table 12 shows the results of different companies. These scores are computed by using the actual and predicted values of returns. It is observed from Table 12 that values of RMSE, MSE, and MAE are quite low, which is an indication of best performance.

However, AK Bank of Turkey's RMSE score is slightly higher when compared to companies from other countries. In addition, for comparison, we repeated the same experiments using the OLS method as shown in Table 13. It is observed from Table 13 that the values of RMSE, MSE,

Table 11: Coefficient outputs for Hong Kong with sentiment.

	Companies	Parameters					
		γ_0	γ_1	γ_2	γ_3	γ_4	γ_5
SLP	China Merchant Bank	−0.0184	−0.0958* (−12.3360)	−0.0036 (−0.3368)	−0.0193** (−2.0588)	−0.1512* (−1.9018)	−0.0428*** (−5.8862)
	Industrial and Commercial Bank	−0.0259	−0.0589* (−5.2261)	−0.0086 (−0.8962)	−0.0197*** (−3.2258)	−0.1119** (−2.5581)	−0.6913*** (−6.3542)
	Ping Insurance Co	0.4591	−0.1638** (−2.5120)	−0.0027 (−1.2250)	−0.0238*** (−2.8960)	−0.1813** (−5.2285)	−0.3442*** (−4.3325)
	HK Index	0.0062	−0.0032*** (−7.8891)	−0.0239* (−1.8251)	−0.0501*** (−4.5520)	−0.0237* (−13.2884)	−0.1295*** (−7.2258)
OLS	China Merchant Bank	−0.0125	−0.0456*** (−4.6320)	−0.0653 (−0.0021)	−0.2350 (−1.3350)	−0.1020 (−1.0050)	−0.4580** (−2.4420)
	Industrial and Commercial Bank	−0.8630	−0.0030* (−1.8060)	−0.0032 (−0.0056)	−0.1120** (−2.3660)	−0.1130 (−0.3340)	−0.4460*** (−3.5620)
	Ping Insurance Co	0.5560	−0.0040 (−1.2050)	0.1120 (0.6670)	−0.5520 (−0.0780)	−0.1140* (−1.6680)	−0.0050** (−2.1220)
	HK Index	0.3360	−0.0010* (−1.6640)	0.4450 (0.6680)	−0.4380 (−0.4450)	−0.0052* (−2.1100)	0.5630** (−2.0050)

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

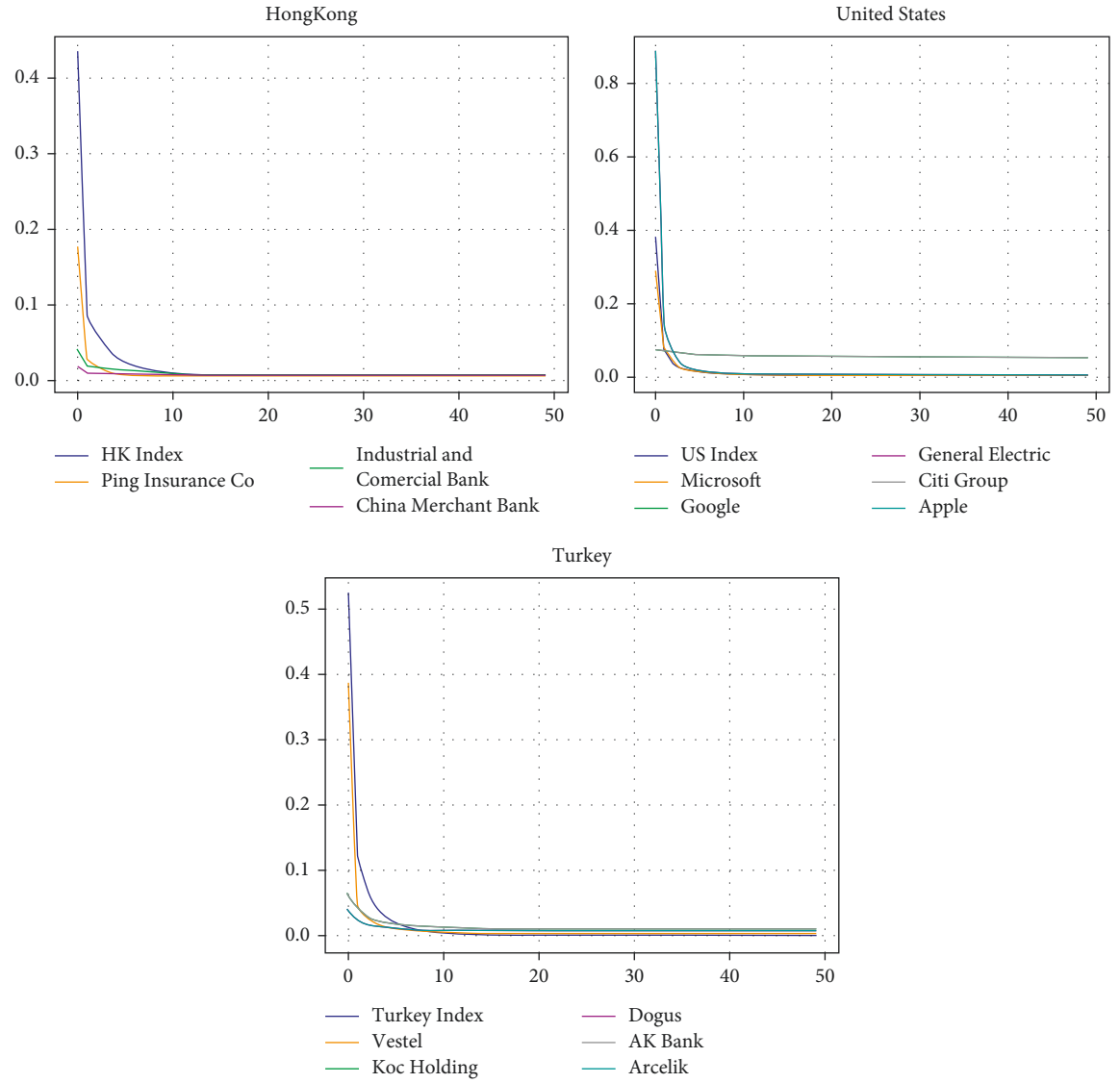

Figure 3: Training loss curves of the companies of different countries including Hong Kong, the United States, and Turkey without sentiments.

Table 12: Results of single layer perceptron for all companies of Hong Kong, the US, and Turkey without sentiment.

	Results of single-layer perceptron		
	RMSE	MSE	MAE
Hong Kong			
HK Index	0.0670	0.0045	0.0450
Ping Insurance Co	0.0664	0.0044	0.0473
Industrial and Commercial Bank	0.0986	0.0097	0.0680
China Merchant Bank	0.0787	0.0062	0.0570
United States			
US Index	0.0555	0.0031	0.0327
Microsoft	0.0552	0.0030	0.0366
Google	0.0589	0.0035	0.0409
General Electric	0.0623	0.0039	0.0411
Citi Group	0.2276	0.0518	0.1730
Apple	0.0706	0.0050	0.0495
Turkey			
BIST index	0.0415	0.0017	0.0041
Vestel	0.0709	0.0050	0.0469
KOC Holdings	0.0796	0.0063	0.0573
Dogus	0.0499	0.0025	0.0211
AK Bank	0.1013	0.0103	0.0746
Arcelik	0.0962	0.0093	0.0684

Table 13: Results of OLS method for all companies of Hong Kong, US, and Turkey without sentiments.

	Results of OLS		
	RMSE	MSE	MAE
Hong Kong			
HK Index	0.0731	0.0053	0.0479
Ping Insurance co	0.0740	0.0055	0.0055
Industrial and Commercial Bank	0.0818	0.0067	0.0589
China Merchant Bank	0.0814	0.0066	0.0592
United States			
US Index	0.0456	0.0021	0.0304
Microsoft	0.0519	0.0027	0.0375
Google	0.0582	0.0034	0.0407
General Electric	0.0659	0.0043	0.0451
Citi Group	0.2305	0.0531	0.1754
Apple	0.0689	0.0048	0.0477
Turkey			
BIST Index	0.0033	1.1012	0.0024
Vestel	0.0600	0.0036	0.0396
KOC Holdings	0.0815	0.0066	0.0594
Dogus	0.0513	0.0026	0.0180
AK Bank	0.1016	0.0103	0.0757
Arcelik	0.0890	0.0079	0.0636

and MAE with the OLS technique are generally the same as with the SLP method. However, for certain companies, the values of error with the OLS approach are higher than with the SLP approach, which demonstrates the feasibility of ANN-based approaches. Furthermore, the SLP is currently based on single-layer, but performance improves when the depth is increased to multi-layers to capture more information from features. The smallest loss values also reflect another realisable value: that predictions become more accurate when macroeconomic factors are considered.

4.5. Results of Predictions with Macroeconomic Factors and Sentiment. We evaluated the model's performance in the second stage by including both sentiments and macroeconomic factors. In this experimental setting, the variables of linear regression include the exchange rate, interest rate, gold index, crude oil prices, and sentiment variable. We trained the single-layer perceptron model with these variables for 50 epochs and performed the task of prediction. All of these experiments are repeated with firms from other countries. The training loss curves of different experiments are depicted in Figure 4.

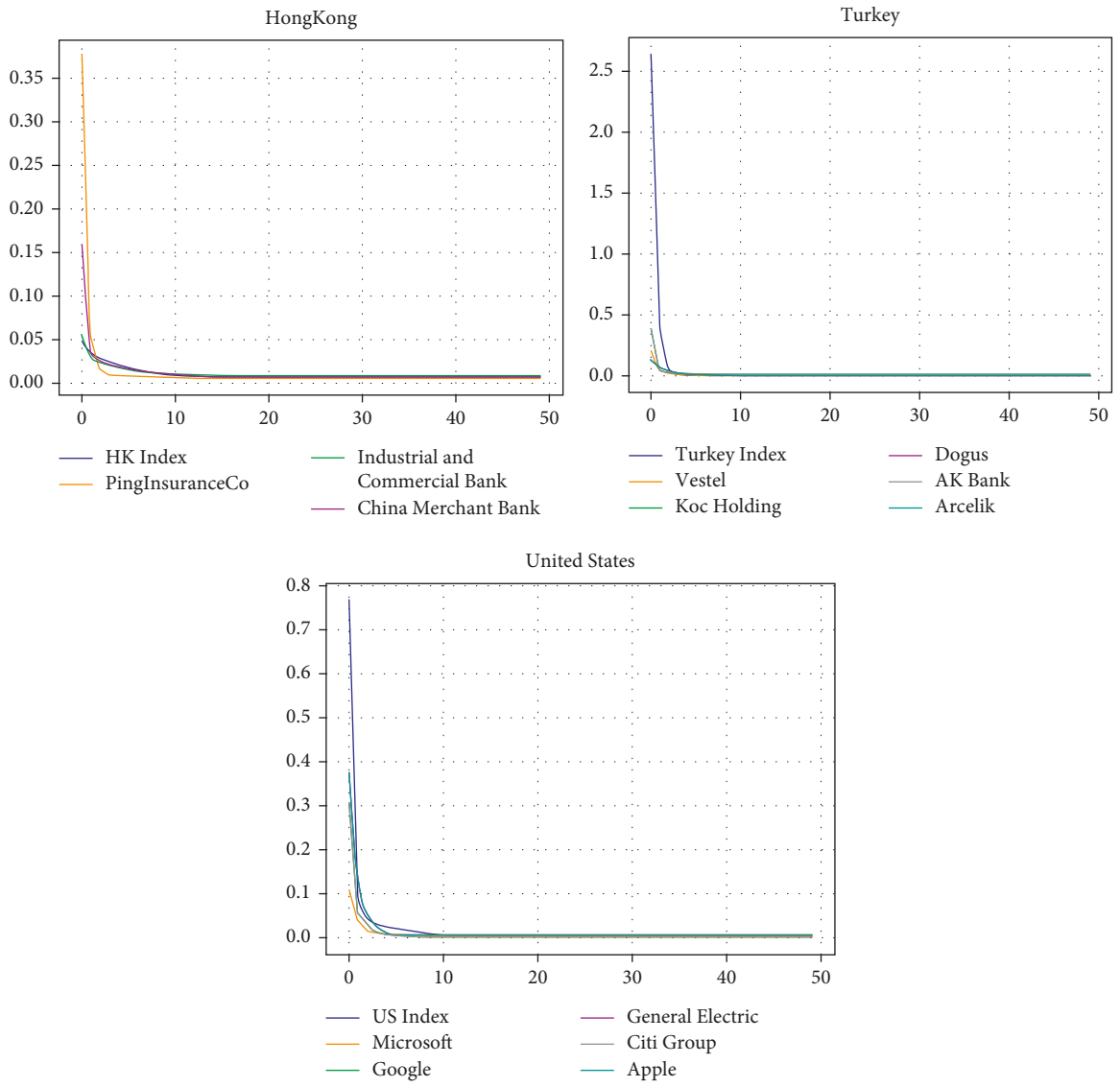

Figure 4: Training loss curves of the companies of different countries including Hong Kong, Turkey, and the United States with sentiments.

The first graph shows the loss curves of Hong Kong companies, the second graph shows the results of Turkey's companies, and the last graph shows the loss curves of the United Nation's companies. Graphs show that SLP models converge relatively rapidly and loss values reach zero. In addition, the results in the form of RMSE, MSE, and MAE of SLP models with the companies of all countries are also computed as given in Table 14. Table 14 contains the findings of companies from various countries. These results are computed by combining actual and predicted return values. Table 14 shows that the values of RMSE, MSE, and MAE are relatively low, indicating excellent performance. As shown in Table 15, we also assessed and extracted the performance of both macroeconomic factors and sentiments using the standard linear regression approach. It has been noticed that the error values with SLP employing sentiments are better than the OLS approach; for example, the MSE value of SLP is 1.10, while the MSE value of OLS is 1.26, which is more than SLP. As a result, it is logically stated that macroeconomic factors and sentiments have a significant effect on returns.

5. Discussion and Comparisons

Stock market forecasting and analyzing stock returns under different factors comprise a developing field in financial research. For corporate organizations, the stock market is an economic driver that mobilizes assets and provides investment opportunities for investors at various levels, such as national, international, and institutional levels, and those who desire to increase their profits without incurring losses. Researchers have employed historical data on stocks in existing research studies to perform stock market analyses or forecasting tasks [17]. However, some research studies have involved the sentiment data for particular events on social media platforms with stock data to more accurately model stock market trends [19–21] because data analytics based on social media plays an important role in countries' stock

Table 14: Results of the SLP method for all companies of Hong Kong, US, and Turkey with sentiments.

	Results of single-layer perceptron		
	RMSE	MSE	MAE
Hong Kong			
HK Index	0.0723	0.0052	0.0541
Ping Insurance co	0.0689	0.0047	0.0495
Industrial and Commercial Bank	0.0873	0.0076	0.0653
China Merchant Bank	0.0859	0.0074	0.0633
United States			
US Index	0.0546	0.0030	0.0333
Microsoft	0.0567	0.0032	0.0380
Google	0.0547	0.0030	0.0394
General Electric	0.0606	0.0037	0.0409
Citi Group	0.0012	1.4564	0.0008
Apple	0.0767	0.0059	0.0524
Turkey			
BIST Index	0.0036	1.2606	0.0026
Vestel	0.0670	0.0045	0.0470
KOC Holdings	0.0807	0.0065	0.0631
Dogus	0.0614	0.0038	0.0215
AK Bank	0.1102	0.0122	0.0858
Arcelik	0.0897	0.0080	0.0673

Table 15: Results of OLS method for all companies of Hong Kong, US, and Turkey with sentiments.

	Results of OLS		
	RMSE	MSE	MAE
Hong Kong			
HK Index	0.0784	0.0062	0.0584
Ping Insurance Co	0.0773	0.0060	0.0541
Industrial and Commercial Bank	0.0852	0.0073	0.0639
China Merchant Bank	0.0799	0.0064	0.0595
United States			
US Index	0.0479	0.0023	0.0319
Microsoft	0.0507	0.0026	0.0368
Google	0.0599	0.0036	0.0414
General Electric	0.0597	0.0036	0.0415
Citi Group	0.0429	0.0018	0.0022
Apple	0.0717	0.0051	0.0496
Turkey			
BIST Index	0.0034	1.1608	0.0025
Vestel	0.0756	0.0057	0.0511
KOC Holdings	0.0828	0.0069	0.0645
Dogus	0.0520	0.0027	0.0228
AK Bank	0.1072	0.0115	0.0844
Arcelik	0.0865	0.0075	0.0673

market trends. All these analyses have been conducted through diverse approaches, of which ANNs and traditional intelligence-based models are the most prevalent. In recent years, the use of stock forecasting models based on artificial intelligence, particularly deep learning algorithms, has grown. Nevertheless, some regression-based machine learning models have also been employed, such as support vector regression. Nonetheless, finding the most optimal methods is a critical field of study.

In the same vein, stock markets reflect a country's economic health; thus, in order to properly assist investors and other shareholders, the effects of macroeconomic variables on stock market returns should be assessed. During stock investment decisions, the existence and unpredictability of macroeconomic factors guide investors with ideas about whether an investment will earn high or lower returns. Changes in macroeconomic variables can considerably influence stock market pricing, stimulating the interest of economists and investors. Hence, the involvement of macroeconomic variables in analyzing stock market trends benefits investors and policymakers because extensive knowledge permits investors to make more informed and wiser decisions. The influence of the relationship between macroeconomic factors and stock returns must be understood to more accurately model stock market trends and patterns. From this perspective, this study contributes to the

existing literature by analyzing the influence on stock returns by considering macroeconomic variables.

In previous studies, this influence has been studied and demonstrated through different statistical and traditional regression methods. However, compared to them, this study proposed a more refined and effective approach using single-layer neural networks to carry out regression analyses. In addition, this study included the EUNS as an additional variable to macroeconomic variables to analyze the stock market returns more accurately.

Furthermore, we analyzed the stock returns of three well-established countries: the US, Turkey, and Hong Kong. Among these countries, we selected the top four or five biggest companies, for which we computed the values of the regression coefficients. The findings demonstrate that the gold index, interest rate, and exchange rate are extremely significant and negative for all these countries. In similar lines, EUNS is also negative and significant.

6. Conclusion

This study investigated the influence of macroeconomic variables (i.e., the gold index, crude oil price, interest rate, and exchange rate) in the context of EUNS on stock market returns. For the empirical process, we used the daily data for all these variables for a specific set of countries: the US, Turkey, and Hong Kong. Later, we employed single-layer neural networks and ordinary least-square regression to calculate the regression coefficients. The results reveal that the gold index, interest rate, and exchange rate are highly significant and negative for all these countries. Moreover, EUNS is also significant and negative in estimating stock returns. We calculated EUNS only for the period of fiscal budget announcements for the US, Turkey, and Hong Kong. As EUNS is negatively significant, it causes panic in stock market participants, which may ultimately lead investors to withdraw their investments. Therefore, regarding the policy implications of this study, it is important to control negative news about the economy that can panic investors during sensitive periods. Similarly, individual investors should have portfolios that include gold and stocks during uncertain periods to avoid abnormal losses. In our future research studies, we intend to expand the dataset on EUN tweets to cover a longer period. Furthermore, data regarding the other macroeconomic variables can also be enhanced.

Data Availability

The datasets are publicly available and will be provided by contacting the corresponding author.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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References

[1] A. Aali-Bujari, F. Venegas-Martínez, and G. Pérez-Lechuga, "Impact of the stock market capitalization and the banking spread in growth and development in Latin American: a panel data estimation with System GMM," *Contaduría y Administración*, vol. 62, no. 5, pp. 1427–1441, 2017.

[2] K. Celebi and M. Hönig, "The impact of macroeconomic factors on the German stock market: evidence for the crisis, pre-and post-crisis periods," *International Journal of Financial Studies*, vol. 7, no. 2, p. 18, 2019.

[3] C. Liang, L. Tang, Y. Li, and Y. Wei, "Which sentiment index is more informative to forecast stock market volatility? Evidence from China," *International Review of Financial Analysis*, vol. 71, Article ID 101552, 2020.

[4] F. Audrino, F. Sigrist, and D. Ballinari, "The impact of sentiment and attention measures on stock market volatility," *International Journal of Forecasting*, vol. 36, no. 2, pp. 334–357, 2020.

[5] W. Jiang, "Applications of deep learning in stock market prediction: recent progress," *Expert Systems with Applications*, vol. 184, Article ID 115537, 2021.

[6] T. K. Lee, J. H. Cho, D. S. Kwon, and S. Y. Sohn, "Global stock market investment strategies based on financial network indicators using machine learning techniques," *Expert Systems with Applications*, vol. 117, pp. 228–242, 2019.

[7] D. P. Gandhmal and K. Kumar, "Systematic analysis and review of stock market prediction techniques," *Computer Science Review*, vol. 34, Article ID 100190, 2019.

[8] H. Yu, L. Fang, and W. Sun, "Forecasting performance of global economic policy uncertainty for volatility of Chinese stock market," *Physica A: Statistical Mechanics and its Applications*, vol. 505, pp. 931–940, 2018.

[9] R. Chaudhary, P. Bakhshi, and H. Gupta, "Volatility in international stock markets: an empirical study during COVID-19," *Journal of Risk and Financial Management*, vol. 13, no. 9, p. 208, 2020.

[10] Z. Jin, Y. Yang, and Y. Liu, "Stock closing price prediction based on sentiment analysis and LSTM," *Neural Computing & Applications*, vol. 32, no. 13, pp. 9713–9729, 2020.

[11] X. Zhang, Y. Zhang, S. Wang, Y. Yao, B. Fang, and P. S. Yu, "Improving stock market prediction via heterogeneous information fusion," *Knowledge-Based Systems*, vol. 143, pp. 236–247, 2018.

[12] M. Balcilar, R. Gupta, and S. M. Miller, "Regime switching model of US crude oil and stock market prices: 1859 to 2013," *Energy Economics*, vol. 49, pp. 317–327, 2015.

[13] S. A. Basher, A. A. Haug, and P. Sadorsky, "Oil prices, exchange rates and emerging stock markets," *Energy Economics*, vol. 34, no. 1, pp. 227–240, 2012.

[14] N. Antonakakis, I. Chatziantoniou, and G. Filis, "Dynamic co-movements of stock market returns, implied volatility and policy uncertainty," *Economics Letters*, vol. 120, no. 1, pp. 87–92, 2013.

[15] Z. Alsalman, "Oil price uncertainty and the US stock market analysis based on a GARCH-in-mean VAR model," *Energy Economics*, vol. 59, pp. 251–260, 2016.

[16] N. Tangjitprom, "The review of macroeconomic factors and stock returns," *International Business Research*, vol. 5, no. 8, p. 107, 2012.

[17] S. M. Idrees, M. A. Alam, and P. Agarwal, "A prediction approach for stock market volatility based on time series data," *IEEE Access*, vol. 7, pp. 17287–17298, 2019.

[18] W. Khan, M. A. Ghazanfar, M. A. Azam, A. Karami, K. H. Alyoubi, and A. S. Alfakeeh, "Stock market prediction using machine learning classifiers and social media, news," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 7, pp. 3433–3456, 2020.

[19] H. S. Lee, "Exploring the initial impact of COVID-19 sentiment on US stock market using big data," *Sustainability*, vol. 12, no. 16, p. 6648, 2020.

[20] H. Maqsood, M. Maqsood, S. Yasmin, I. Mehmood, J. Moon, and S. Rho, "Analyzing the stock exchange markets of eu nations: a case study of brexit social media sentiment," *Systems*, vol. 10, no. 2, p. 24, 2022.

[21] O. Oyebode and R. Orji, "Social media and sentiment analysis: the Nigeria presidential election 2019," in *Proceedings of the 2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference*, pp. 0140–0146, IEMCON), Vancouver, BC, Canada, October 2019.

[22] P. Y. Hao, "Predicting the trends of stock price by social networks and fuzzy deep support vector machine," in *Proceedings of the 2021 IEEE Symposium Series on Computational Intelligence*, pp. 01–08, SSCI), Orlando, FL, USA, December 2021.

[23] H. Murtaza and R. Ali, "Impact of major political events on stock market returns of Pakistan," *Public Policy and Administration Research*, vol. 5, pp. 68–84, 2015.

[24] J. Khan and I. Khan, "The impact of macroeconomic variables on stock prices: a case study of Karachi Stock Exchange," *Journal of Economics and Sustainable Development*, vol. 9, pp. 15–25, 2018.

[25] B. Ndlovu, F. Faisa, N. G. Resatoglu, and T. Türsoy, "The Impact Macroeconomic Variables on Stock Returns: A Case of the Johannesburg Stock Exchange," *Romanian Statistical Review*, vol. 2018, 2018.

[26] R. K. Dash, T. N. Nguyen, K. Cengiz, and A. Sharma, "Fine-tuned support vector regression model for stock predictions," *Neural Computing and Applications*, pp. 1–15, 2021.

[27] E. P. Torres, M. Hernández-Álvarez, E. A. Torres Hernández, and S. G. Yoo, "Stock market data prediction using machine learning techniques," in *Proceedings of the International Conference on Information Technology & Systems*, pp. 539–547, Quito, Ecuador, February 2019.

[28] J. Ayala, M. García-Torres, J. L. V. Noguera, F. Gómez-Vela, and F. Divina, "Technical analysis strategy optimization using a machine learning approach in stock market indices," *Knowledge-Based Systems*, vol. 225, Article ID 107119, 2021.

[29] S. Mokhtari, K. K. Yen, and J. Liu, "Effectiveness of Artificial Intelligence in Stock Market Prediction Based on Machine Learning," arXiv preprint arXiv:2107.01031, 2021.

[30] M. Bukhari, K. B. Bajwa, S. Gillani et al., "An efficient gait recognition method for known and unknown covariate conditions," *IEEE Access*, vol. 9, pp. 6465–6477, 2021.

[31] M. Maqsood, M. Bukhari, Z. Ali et al., "A residual-learning-based multi-scale parallel-convolutions-assisted efficient CAD system for liver tumor detection," *Mathematics*, vol. 9, no. 10, p. 1133, 2021.

[32] M. Maqsood, S. Yasmin, I. Mehmood, M. Bukhari, and M. Kim, "An efficient DA-Net architecture for lung nodule segmentation," *Mathematics*, vol. 9, no. 13, p. 1457, 2021.

[33] M. Hiransha, G. Ea, V. K. Menon, and S. Kp, "NSE stock market prediction using deep-learning models," *Procedia Computer Science*, vol. 132, pp. 1351–1362, 2018.

[34] A. Moghar and M. Hamiche, "Stock market prediction using LSTM recurrent neural network," *Procedia Computer Science*, vol. 170, pp. 1168–1173, 2020.

[35] M. A. I. Sunny, M. M. S. Maswood, and A. G. Alharbi, "Deep learning-based stock price prediction using LSTM and bi-directional LSTM model," in *Proceedings of the 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference*, pp. 87–92, NILES), Giza, Egypt, October 2020.

[36] X. Li, P. Wu, and W. Wang, "Incorporating stock prices and news sentiments for stock market prediction: a case of Hong Kong," *Information Processing & Management*, vol. 57, no. 5, Article ID 102212, 2020.

[37] I. Gupta, T. K. Madan, S. Singh, and A. K. Singh, "HiSA-SMFM: historical and sentiment analysis based stock market forecasting model," arXiv preprint arXiv:2203.08143, 2022.

[38] H. Chung and K.-s. Shin, "Genetic algorithm-optimized long short-term memory network for stock market prediction," *Sustainability*, vol. 10, p. 3765, 2018.

[39] H. Chung and K.-s. Shin, "Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction," *Neural Computing & Applications*, vol. 32, no. 12, pp. 7897–7914, 2020.

[40] K. Zhang, G. Zhong, J. Dong, S. Wang, and Y. Wang, "Stock market prediction based on generative adversarial network," *Procedia Computer Science*, vol. 147, pp. 400–406, 2019.

[41] Y. Li, P. Ni, and V. Chang, "Application of deep reinforcement learning in stock trading strategies and stock forecasting," *Computing*, vol. 102, no. 6, pp. 1305–1322, 2020.

[42] R. Benkraiem, A. Lahiani, A. Miloudi, and M. Shahbaz, "New insights into the US stock market reactions to energy price shocks," *Journal of International Financial Markets, Institutions and Money*, vol. 56, pp. 169–187, 2018.

[43] X. Shi, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo, "Convolutional LSTM network: a machine learning approach for precipitation nowcasting," arXiv preprint arXiv:1506.04214, 2015.

[44] W. Huang, Y. Nakamori, and S.-Y. Wang, "Forecasting stock market movement direction with support vector machine," *Computers & Operations Research*, vol. 32, no. 10, pp. 2513–2522, 2005.

[45] R. Lawrence, *Using neural networks to forecast stock market prices*, pp. 2006–2013, University of Manitoba, Canada, 1997.

[46] A. E. Khedr, N. Yaseen, and N. Yaseen, "Predicting stock market behavior using data mining technique and news sentiment analysis," *International Journal of Intelligent Systems and Applications*, vol. 9, no. 7, pp. 22–30, 2017.

[47] B. Billah, M. L. King, R. D. Snyder, and A. B. Koehler, "Exponential smoothing model selection for forecasting," *International Journal of Forecasting*, vol. 22, no. 2, pp. 239–247, 2006.

[48] C. O. Omodero and S. Mlanga, "Evaluation of the impact of macroeconomic variables on stock market performance in Nigeria," *Business and Management Studies*, vol. 5, no. 2, pp. 34–44, 2019.

[49] M. Bukhari, S. Yasmin, S. Sammad, A. A. Abd El-Latif, and A. Ahmed, "A deep learning framework for leukemia cancer detection in microscopic blood samples using squeeze and excitation learning," *Mathematical Problems in Engineering*, vol. 2022, pp. 1–18, Article ID 2801227.

[50] F. Nazir, M. N. Majeed, M. A. Ghazanfar, and M. Maqsood, "Mispronunciation detection using deep convolutional neural network features and transfer learning-based model for Arabic phonemes," *IEEE Access*, vol. 7, pp. 52589–52608, 2019.

[51] L. Bachmeier, "Monetary policy and the transmission of oil shocks," *Journal of Macroeconomics*, vol. 30, no. 4, pp. 1738–1755, 2008.

[52] C.-C. Lee, C.-C. Lee, and S.-L. Ning, "Dynamic relationship of oil price shocks and country risks," *Energy Economics*, vol. 66, pp. 571–581, 2017.

[53] C.-C. Lee and Y.-B. Chiu, "Nuclear energy consumption, oil prices, and economic growth: evidence from highly industrialized countries," *Energy Economics*, vol. 33, no. 2, pp. 236–248, 2011.

[54] J. C. Reboredo and M. A. Rivera-Castro, "Wavelet-based evidence of the impact of oil prices on stock returns," *International Review of Economics & Finance*, vol. 29, pp. 145–176, 2014.

[55] E. A. Toparlı, A. N. Çatık, and M. Balcılar, "The impact of oil prices on the stock returns in Turkey: a TVP-VAR approach," *Physica A: Statistical Mechanics and its Applications*, vol. 535, Article ID 122392, 2019.

[56] M. K. Khan, J.-Z. Teng, and M. I. Khan, "Asymmetric impact of oil prices on stock returns in Shanghai stock exchange: evidence from asymmetric ARDL model," *PLoS One*, vol. 14, no. 6, Article ID e0218289, 2019.

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Research Article

Driven Force Induced Bifurcation Delay on the Chaotic Financial System

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To understand the variations in the financial characteristics, we examine the dynamical behaviors by considering the chaotic financial model with external force. First, the dynamical characteristics are analyzed by introducing the external driven force in the price index with commodity demand. We discover that the presence of an external force causes the alternate occurrence of oscillatory and steady states as a function of time. Interestingly, we find the existence of bifurcation delay (BD) during the transition from oscillatory (OS) to steady state (SS) or vice versa. Bifurcation delay is a phenomenon in which the bifurcation does not occur at the actual bifurcation point but rather at a later time, which is referred to as bifurcation delay. To confirm the delay in bifurcation, we estimate the actual bifurcation point and compare it to the observed bifurcation transition. Furthermore, to understand the variations in the bifurcation delay, we estimate the delay time between each consecutive cycle and find random fluctuations in the BD. Following that, the BD is virtualized via a transformed phase portrait. In addition, we show decreasing the value of average BD while increasing the frequency of external forcing. Second, the presence of BD is explored by incorporating external forces into the investment demand with unit investment cost. We discover the existence of a similar phenomenon with a constant bifurcation delay.

1. Introduction

Economic dynamics has found the interest of many researchers due to the rapid growth of the economy. Moreover, small changes in the environment can have a significant impact on micro and macroeconomics, resulting in irregular economic development [1–3]. For instance, unforeseeable global events such as wars, disasters, epidemics, and so on may provoke unanticipated changes in the investment environment or affect the fluctuations of economic development [4]. As [5] a result, modern economic research is increasingly interested in developing nonlinear financial models that incorporate a variety of relevant parameters such as interest rates, prices, saving amounts, and commodity demand, among others [6–8]. Typically, savings are determined by wealth and income. Investment and saving are separate decisions, and the relationship between these two is discussed in Ref. [9].

Besides, the dynamical behavior of the financial system has recently received special attention. For instance, the existence of periodic, quasiperiodic, strange nonchaotic, chaos behaviors and their transition route were described using a simple 3D financial system [10]. The construction of the 4D chaotic finance model and its significance were detailed [11]. The dynamics of the financial system have also been investigated by introducing investment incentives into

3D systems, resulting in a 4D financial system. The chaotic dynamics were observed using such a system with fractional order, which was confirmed using the 0 − 1 test [12]. Further, the chaotic behavior was well studied in the fractional financial system with time-delay [13–16]. In addition, the control of the 4D hyperchaotic finance system was analyzed by adding an inverse optimal controller [17]. Thus, the dynamics of the financial system were thoroughly investigated by implementing a fractional order and introducing single and two delays into the financial systems [16].

On the other hand, many nonlinear systems can exhibit [18–23] slow-fast dynamics that can be modeled as slow-fast systems [18,20]. Such slow-fast systems exhibit many intriguing phenomena like bursting, mixed-mode oscillations, and bifurcation delay or slow passage effect, among others. Originally, the occurrence of bifurcation delay via Hopf bifurcation was identified by Baer et al. in a fast-slow system of FitzHugh–Nagumo (FHN) model [24]. Later, such occurrences were reported via various other bifurcation routes, including the pitchfork and saddle-node [25–27]. Further, the delayed bifurcation was reported in reaction-diffusion systems, as well as the bistable thermoacoustic system [28–30].

Furthermore, bifurcation delay is a fascinating phenomenon that can be found in a wide range of natural and engineering systems [31–34]. The delay in which the bifurcation occurs can be referred to as bifurcation delay. As a consequence, the existence of dynamic bifurcations as well as strange nonchaotic phenomena was delineated in [35] with single or two frequency driven nonlinear oscillators that is followed by the impact of propagation or processing delay on bifurcation delay reported in a network of slow-fast FHN oscillators [36]. It was identified that there is existence of various collective states including synchronization, chimera, and traveling wave when perturbing the frequency of a single node of the oscillator [37]. Furthermore, the effect of fractional order and noisy parameter on BD was also analyzed [38]. According to the above studies, the phenomenon of bifurcation delay has been identified in biological, physical, and chemical systems but has not yet been investigated in the financial system. With the above motivation, we investigated whether the chaotic financial model can exhibit the bifurcation delay phenomenon when introducing the external force into certain parameters. Since the price index with commodity demand and investment cost with unit investment cost is time-dependent, we analyzed the dynamical characteristics of the chaotic financial model by adding the external driving force with it.

The remaining sections of the article are as follows: In Sec. 2, we first present the dynamical model by introducing the driving force in the price index with commodity demand. We specifically discuss the existence of bifurcation delay and its characteristics. Followed by this, the occurrence of constant bifurcation delay is discussed in Sec. 3 when introducing the driving force into the investment demand with unit investment cost. Finally, in Section 4, the observed results are summarized.

2. Effect of Time-Varying Price Index with Commodity Demand

We consider a chaotic financial (CF) model as in Ref. [16] to exemplify the bifurcation delay in economic growth and its characteristics. Since the commodity demand and price indexes can vary depending on external factors, we modified the system to be a driven chaotic financial (DCF) model by including external forcing. The corresponding model equation is as follows:

$$\begin{aligned} \dot{x} &= z + (y - \alpha)x, \\ \dot{y} &= 1 - \beta y - x^2 - \beta x y, \\ \dot{z} &= -x - \gamma f(t) z, \end{aligned} \tag{1}$$

where x, y, and z are the system parameters that represent the interest rate, the investment demand, and price index, respectively. The constant parameters α, β, and γ denote the saving amount, the unit investment cost, and the elasticity of commodity demand, respectively. $f(t)$ is the external forcing, defined as $f(t) = (1 + f \sin(\omega t))$, where f is the amplitude of external force or the drive parameters and ω is the forcing frequency. The parameters values are fixed as $\alpha = 2.0$, $\beta = 0.1$, and $\gamma = 1.0$.

2.1. Bifurcation Delay (BD) and Its Transition. To demonstrate the occurrence of bifurcation delay (BD), we showed the time evolution of the x variable (represented by the red line) overlapped by $f(t) = 1 + f \sin(\omega t)$ (represented by the black line) in Figure 1(a). The time series signal clearly shows the continuous repetition of the oscillatory and steady state as a function of time. Further, to understand the bifurcation transition, the one-parameter bifurcation diagram (using XPPAUT Ref. [39]) is portrayed in Figure 1(b) as a function of f. The transition from an unstable steady (US) state to a stable steady (SS) state exists via subcritical Hopf bifurcation (HB). We also observed that unstable oscillations (OS) coexist with a stable steady state. From Figure 1(b), we obtained that the transition to steady state occurs at the Hopf bifurcation point $HB = -0.205$.

In addition to displaying the bifurcation delay clearly, we plotted a zoomed view of the time series signal with $f(t)$ as in Figure 1(c). The dashed line represents the Hopf bifurcation line, which is represented by using a point where HB occurs. Typically, the actual bifurcation occurs when the Hopf bifurcation point intersects the function $f(t)$, and then a steady state emerges. t_{HB_1} and t_{HB_2} are the time of first and second actual Hopf bifurcation which arise during the transition from *OS* to *SS* and *SS* to *OS*, respectively. But we observed that the transition to *SS* occurs at a time t_S and OS occurs at t_O. Therefore, the first and second bifurcation delay during *OS* state to *SS* state and *SS* state to *OS* state are obtained as $\tau_{b_1} = t_{HB_1} - t_S$ and $\tau_{b_2} = t_{HB_2} - t_O$, where t_S and t_O are the delay in bifurcation during the transition to steady state and oscillatory state, respectively. From the observation, it is clear that the existence of bifurcation delays is due to driving force. In the

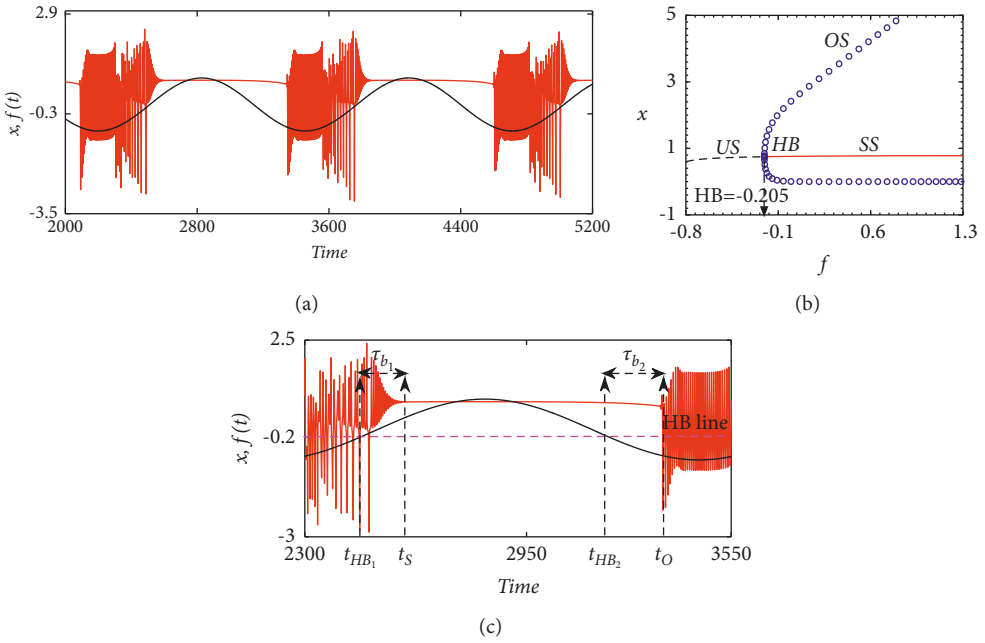

FIGURE 1: (a) Time series signal of a driven chaotic financial system overlapped with external force $f(t)$. (b) One-parameter bifurcation diagram (using XPPAUT) as a function of forcing amplitude. US and SS are unstable and stable steady state represented by dashed (black) and solid (red) lines, respectively. OS is the oscillatory state (denoted blue open circles) and HB is the Hopf bifurcation point. (c) Zoomed view of time series x and external force $f(t)$, where $\tau_{b_1} = t_{HB_1 - t_S}$ and $\tau_{b_2} = t_{HB_2 - t_O}$. Other system parameters are $\alpha = 2.0$, $\beta = 0.1$, $f = 0.85$, $\omega = 0.02$, and $\gamma = 2.5$.

following, we analyze whether the bifurcation delays τ_{b_1} and τ_{b_2} manifest fluctuations in long time series signals and their probability density functions.

2.2. Variation of BD and Its Characteristics. To determine the fluctuations in the bifurcation delay, we computed the bifurcation delay for each subsequent periodic cycle (n) in the long time series signals in Figure 2. In particular, Figures 2(a) and 2(c) are plotted for variation of first and second bifurcation delays τ_{b_1} and τ_{b_2}. We can see the random fluctuations (irregular motion) in both bifurcation delays τ_{b_1} as well as τ_{b_2}. However, it is also clear that the average mean value of the bifurcation delay is distributed around $(\tau_{b_1} = 134)$ and $(\tau_{b_2} = 149)$ for first and second BD, respectively. Furthermore, we estimate the probability distribution function (PDF) for the signal corresponding to Figures 2(a) and 2(c) in 2(b) and 2(d). The probability distribution function is estimated by finding the number of events (each point in the signal can be considered as an event) in the signal lying between a specific magnitude of bifurcation delay in the entire cycles in time series signal. It is observed that both the BDs follow the Gaussian distribution in the probability distribution function.

For a more clear understanding of the delay in bifurcation, we plotted transformed phase portrait in $(f(t), x)$ space as in Figure 3. Furthermore, to detect the bifurcation point, the bifurcation diagram (Figure 1(b)) is superimposed on the transformed phase portrait. The bifurcation point HB is where the actual bifurcation transition takes place. From Figure 3, it is evident that there is a delay in bifurcation, which means that the bifurcation OS-SS transition does not occur at the actual bifurcation point but rather after some time. Thus, it clearly depicts the occurrence of bifurcation delay.

In addition, the average bifurcation delay is estimated in Figure 4 by varying the forcing frequency. We can observe that the magnitude of bifurcation delays τ_{b_1} is reduced when increasing the frequency ω, as seen in Figure 4(a). We can note the second BD τ_{b_2} also manifests similar dynamical behaviors as shown in Figure 4(b).Futhermore, we also look the emergence of bifurcation delay when applying external forcing as time-varying investment demand with unit investment cost in the following section.

3. Effect of Time-Varying Investment Demand with Unit Investment Cost

In addition to the preceding analysis, in realistic situations, the investment demand with unit investment cost can fluctuate over time. As a result, we include the additional external force $f(t)$ in the β variable, and the dynamical model could be written as

$$\begin{aligned} \dot{x} &= z + (y - \alpha)x, \\ \dot{y} &= 1 - \beta f(t) y - x^2 - \beta x y, \\ \dot{z} &= -x - \gamma z. \end{aligned} \tag{2}$$

To show the dynamical transition, we plotted the one-parameter bifurcation diagram in Figure 5(a) by varying the forcing amplitude f. The bifurcation transition illustrates that the transition from stable periodic oscillation to the

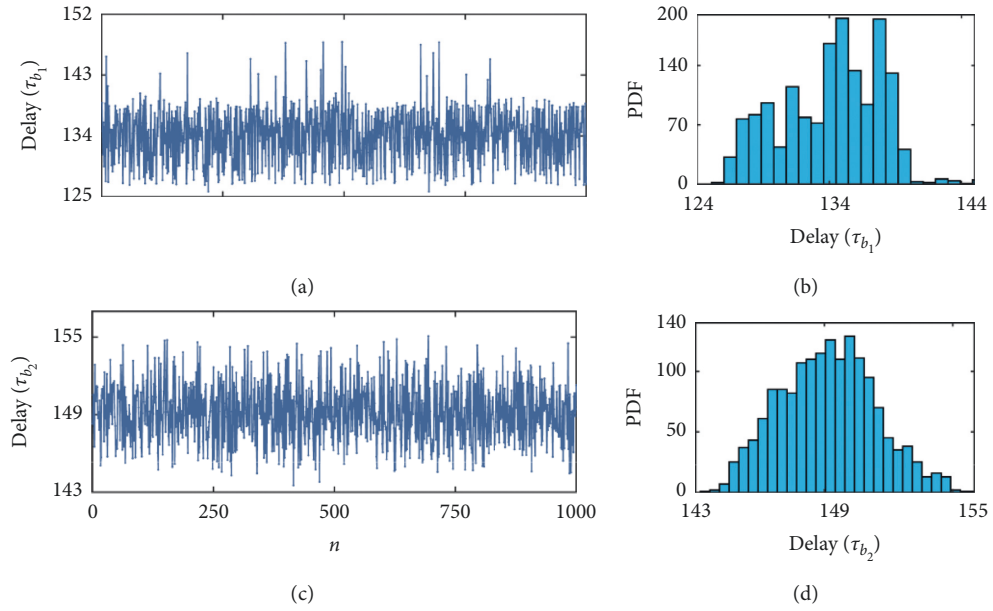

FIGURE 2: Bifurcation delay of consecutive periodic cycles for (a) first bifurcation delay τ_{b_1} and (c) second bifurcation delay τ_{b_2}. (b) and (d) are the corresponding probability distribution of both the bifurcation delays. Here, the average mean bifurcation delay is (a) $\tau_{b_1} = 134$ and (b)$\tau_{b_2} = 149$. Other parameter values are fixed same as in Figure 1.

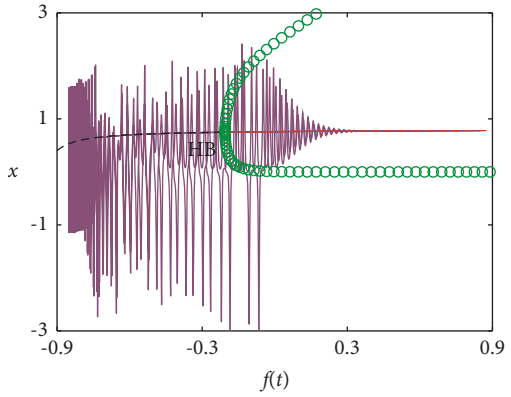

FIGURE 3: Transformed phase portrait on the plane of $(f(t) - x)$. In the figure, the HB is the Hopf bifurcation point. The red and black dashed lines correspond to stable and unstable steady state, respectively. The green unfilled points represent the amplitude of the limit cycle oscillation. Other parameter values are fixed same as in Figure 1.

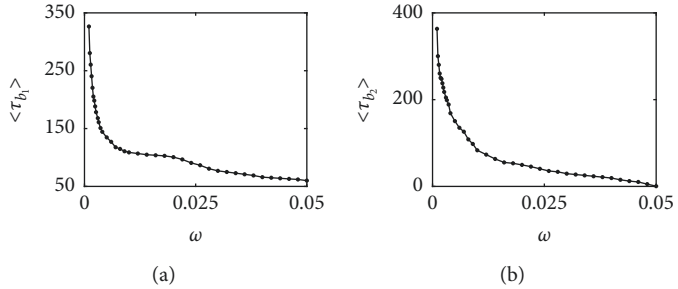

FIGURE 4: Average bifurcation delay as a function of forcing frequency (ω) for (a) first Hopf bifurcation $\langle \tau_{b_1} \rangle$ and (b) second Hopf bifurcation $\langle \tau_{b_2} \rangle$. Other parameter values are fixed same as in Figure 1.

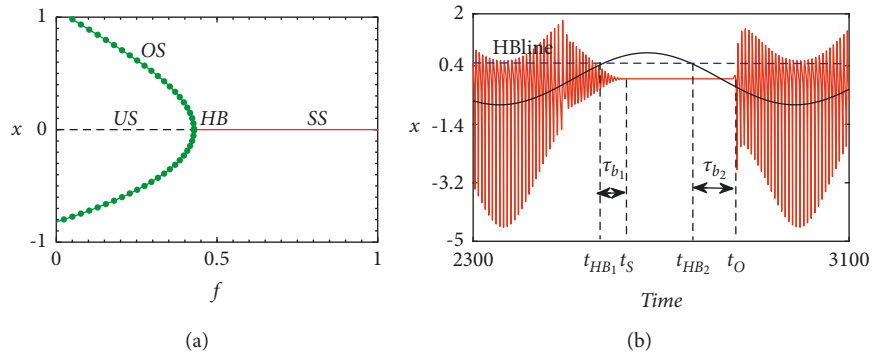

Figure 5: (a) One-parameter bifurcation diagram as a function of amplitude of external forcing f. Green filled circles represent the stable oscillations. The dashed (black) and solid (red) lines denote the unstable and stable steady state, respectively. (b) Time series signal overlapped with the function $f(t)$. Other parameter values are fixed same as in Figure 1.

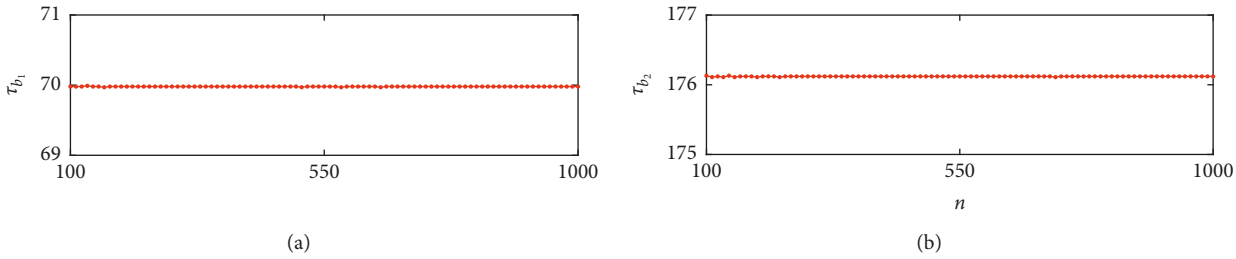

Figure 6: Variation in bifurcation delay (a)τ_{b_1} and (b)τ_{b_2} for each consecutive periodic cycles n.

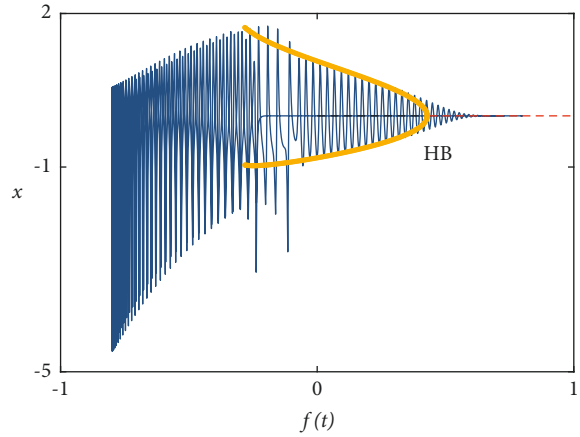

Figure 7: Transformed phase portrait on the plane of $(f(t) - x)$. In the figure, the HB is the supercritical Hopf bifurcation point, where the black line corresponds to stable trivial steady state and the green line represents the amplitude of the limit cycle oscillation. Other parameter values are fixed same as in Figure 1.

stable steady state occurs via Hopf bifurcation. Since the transition from stable limit cycle oscillation to the stable steady state, the associated bifurcation point is supercritical Hopf bifurcation, and the Hopf bifurcation point is identified as $HB = 0.4286$. Using the observed HB point, the HB line (denoted by dashed line) is plotted in Figure 5(b). Comparing the time series signal with actual bifurcation point (intersection of $f(t)$ with t_{HB_1} or t_{HB_2}), we observed that there is the delay in bifurcation $\tau_{b_1} = t_{HB_1} - t_S$ and $\tau_{b_2} = t_{HB_2} - t_O$ during the *OS* state to *SS* state or *OS* state to *SS* state, respectively.

Further, it is also inspected whether the bifurcation delay can have any fluctuations in the successive cycle in the time series signal. Therefore, the bifurcation delays τ_{b_1} and τ_{b_2} of each consecutive cycles are portrayed in Figures 6(a) and 6(b). Due to periodic repetition of oscillation, we observed constant bifurcation delay during *OS*-*SS*(τ_{b_1}) and *SS*-*OS*(τ_{b_2}) transitions.

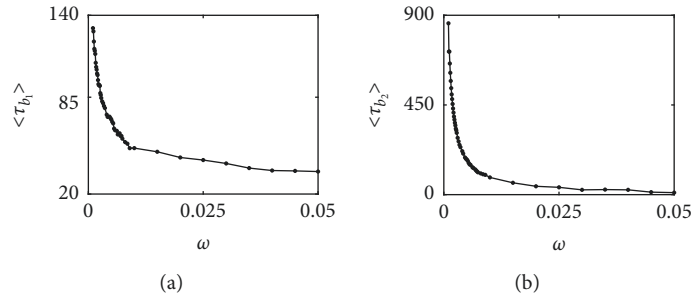

FIGURE 8: Average bifurcation delay as a function of forcing frequency (ω) for (a) first Hopf bifurcation $\langle \tau_{b1} \rangle$ and (b) second Hopf bifurcation $\langle \tau_{b2} \rangle$. Other parameter values are fixed same as in Figure 1.

Following that, the transformed phase portrait is illustrated in $(f(t), x)$ space by overlapping bifurcation plot (shown in Figure 5(a)) to show the delay in bifurcation during the transition from the oscillatory to the steady state. Figure 7 depicts the transition to SS occurring after the actual (HB) bifurcation. Thus, it is clear that the occurrence of bifurcation delay while the transition from oscillatory to steady state.As shown in Figure 4, the average bifurcation delays $\langle \tau_{b1} \rangle$ and $\langle \tau_{b2} \rangle$ decrease as forcing frequency increases, as shown in Figures 8(a) and 8(b).

4. Conclusion

In this study, we have investigated the influence of a time-varying parameter in a chaotic financial model. First, we explored the dynamical behavior of the price index with commodity demand by applying external forcing. Surprisingly, we discovered that the external force had a bifurcation delay in the system. When the bifurcation transition to the steady state or oscillatory state occurs, some delay time can be found as bifurcation delay. We discovered that the price index with commodity demand can result in the BD, which shows random fluctuations in each successive cycle. The relevant probability distribution function (PDF) was also estimated, and we discovered that it follows the Gaussian distribution function. The existence of BD was also investigated using the transformed phase portrait, which clearly shows that the transition from OS to SS occurs after some time when compared to the actual bifurcation point. In addition, we carried out a similar analysis by incorporating external forces in investment demand with unit investment cost. In the time evolution of the signal, we detected a continuous bifurcation delay between each successive cycle. Using the transformed phase portrait, the BD was further validated. Finally, it was discovered that similar to the prior case, raising the frequency range reduces the range of bifurcation delay. Thus, based on the observations, one may infer that an external effect on a certain parameter may produce a bifurcation delay in a chaotic financial system. Our research will offer insight into the bifurcation transition in financial systems.

Data Availability

Data generated during the current study will be made available at reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest in publishing this paper.

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References

[1] P. Tankov, "Financial modelling with jump processes," Chapman and Hall/CRC, Boca Raton, FL, USA, 2003.
[2] M. Kalecki, *Theory of Economic Dynamics*, Routledge, England. UK, 2013.
[3] M. Jun-hai and C. Yu-Shu, "Study for the bifurcation topological structure and the global complicated character of a kind of nonlinear finance system (I)," *Applied Mathematics and Mechanics*, vol. 22, no. 11, pp. 1240–1251, 2001.
[4] A. C. L. Chian, "Nonlinear dynamics and chaos in macroeconomics," *International Journal of Theoretical and Applied Finance*, vol. 03, pp. 601-602, 2000.
[5] A. Serletis, "Is there chaos in economic time series?" *Canadian Journal of Economics*, vol. 29, pp. S210–S212, 1996.
[6] C. Cantore and P. Levine, "Getting normalization right: dealing with 'dimensional constants' in macroeconomics," *Journal of Economic Dynamics and Control*, vol. 36, no. 12, pp. 1931–1949, 2012.
[7] W. Szuminski, "Integrability analysis of chaotic and hyperchaotic finance systems," *Nonlinear Dynamics*, vol. 94, no. 1, pp. 443–459, 2018.
[8] C. Ma and X. Wang, "Hopf bifurcation and topological horseshoe of a novel finance chaotic system," *Communications in Nonlinear Science and Numerical Simulation*, vol. 17, no. 2, pp. 721–730, 2012.
[9] J. L. Esso and Y. Keho, "The savings-investment relationship: cointegration and causality evidence from Uemoa countries," *International Journal of Economics and Finance*, vol. 2, no. 1, pp. 174–181, 2010.
[10] Q. Gao and J. Ma, "Chaos and Hopf bifurcation of a finance system," *Nonlinear Dynamics*, vol. 58, no. 1-2, pp. 209–216, 2009.

[11] D. Kumar and S. Kumar, "Construction of four dimensional chaotic finance model and its applications," *International Journal of Pure and Applied Mathematics*, vol. 118, no. 22, pp. 1171–1187, 2018.

[12] B. Xin and Y. Li, "0–1 test for chaos in a fractional order financial system with investment incentive," *In Abstract and Applied Analysis*, vol. 2013, Article ID 876298, 10 pages, 2013.

[13] W. C. Chen, "Nonlinear dynamics and chaos in a fractional-order financial system," *Chaos, Solitons & Fractals*, vol. 36, no. 5, pp. 1305–1314, 2008.

[14] Y. Xu and Z. He, "Synchronization of variable-order fractional financial system via active control method," *Open Physics*, vol. 11, no. 6, pp. 824–835, 2013.

[15] Z. Wang, X. Huang, and G. Shi, "Analysis of nonlinear dynamics and chaos in a fractional order financial system with time delay," *Computers & Mathematics with Applications*, vol. 62, no. 3, pp. 1531–1539, 2011.

[16] G. Kai, W. Zhang, Z. Jin, and C. Z. Wang, "Hopf bifurcation and dynamic analysis of an improved financial system with two delays. Complexity, 2020," 2020.

[17] C. Chen, T. Fan, and B. Wang, "Inverse optimal control of hyperchaotic finance system," *World Journal of Modelling and Simulation*, vol. 10, no. 2, pp. 83–91, 2014.

[18] E. M. Izhikevich, "Neural excitability, spiking and bursting," *International journal of bifurcation and chaos*, vol. 10, no. 6, pp. 1171–1266, 2000.

[19] G. D. Leutcho, J. Kengne, L. K. Kengne, A. Akgul, V. T. Pham, and S. Jafari, "A novel chaotic hyperjerk circuit with bubbles of bifurcation: mixed-mode bursting oscillations, multistability, and circuit realization," *Physica Scripta*, vol. 95, no. 7, Article ID 075216, 2020.

[20] E. Benoit, "(2006," *Dynamic Bifurcations: Proceedings of a Conference Held in Luminy*, Springer, New York, NY, USA, 1990.

[21] X. Han, Q. Bi, P. Ji, and J. Kurths, "Fast-slow analysis for parametrically and externally excited systems with two slow rationally related excitation frequencies," *Physical Review E*, vol. 92, no. 1, Article ID 012911, 2015.

[22] M. P. Asir, D. Premraj, and K. Sathiyadevi, "Complex mixed-mode oscillations in oscillators sharing nonlinearity," *The European Physical Journal Plus*, vol. 137, no. 2, pp. 282–310, 2022.

[23] H. Wu, Y. Ye, M. Chen, Q. Xu, and B. Bao, "Extremely slow passages in low-pass filter-based memristive oscillator," *Nonlinear Dynamics*, vol. 97, no. 4, pp. 2339–2353, 2019.

[24] S. M. Baer, T. Erneux, and J. Rinzel, "The slow passage through a Hopf bifurcation: delay, memory effects, and resonance," *SIAM Journal on Applied Mathematics*, vol. 49, no. 1, pp. 55–71, 1989.

[25] R. Haberman, "Slow passage through the nonhyperbolic homoclinic orbit associated with a subcritical pitchfork bifurcation for Hamiltonian systems and the change in action," *SIAM Journal on Applied Mathematics*, vol. 62, no. 2, pp. 488–513, 2001.

[26] D. Premraj, K. Suresh, T. Banerjee, and K. Thamilmaran, "An experimental study of slow passage through Hopf and pitchfork bifurcations in a parametrically driven nonlinear oscillator," *Communications in Nonlinear Science and Numerical Simulation*, vol. 37, pp. 212–221, 2016.

[27] D. C. Diminnie and R. Haberman, "Slow passage through homoclinic orbits for the unfolding of a saddle-center bifurcation and the change in the adiabatic invariant," *Physica D: Nonlinear Phenomena*, vol. 162, no. 1-2, pp. 34–52, 2002.

[28] J. C. Tzou, M. J. Ward, and T. Kolokolnikov, "Slowly varying control parameters, delayed bifurcations, and the stability of spikes in reaction–diffusion systems," *Physica D: Nonlinear Phenomena*, vol. 290, pp. 24–43, 2015.

[29] S. Tandon, S. A. Pawar, S. Banerjee, A. J. Varghese, P. Durairaj, and R. I. Sujith, "Bursting during intermittency route to thermoacoustic instability: effects of slow–fast dynamics," *Chaos*, vol. 30, no. 10, Article ID 103112, 2020.

[30] V. R. Unni, E. A. Gopalakrishnan, K. S. Syamkumar, R. I. Sujith, E. Surovyatkina, and J. Kurths, "Interplay between random fluctuations and rate dependent phenomena at slow passage to limit-cycle oscillations in a bistable thermoacoustic system," *Chaos*, vol. 29, no. 3, Article ID 031102, 2019.

[31] S. Shaukat, A. L. I. Arshid, A. Eleyan, S. A. Shah, and J. Ahmad, "Chaos theory and its application: an essential framework for image encryption," *Chaos Theory and Applications*, vol. 2, no. 1, pp. 17–22, 2020.

[32] G. Kai, W. Zhang, Z. C. Wei, J. F. Wang, and A. Akgul, "Hopf bifurcation, positively invariant set, and physical realization of a new four-dimensional hyperchaotic financial system," *Mathematical Problems in Engineering*, vol. 2017, Article ID 2490580, 2017.

[33] M. A. Jun, "Chaos theory and applications: the physical evidence, mechanism are important in chaotic systems," *Chaos Theory and Applications*, vol. 4, no. 1, pp. 1–3, 2022.

[34] J. Sprott, "Do we need more chaos examples?" *Chaos Theory and Applications*, vol. 2, no. 2, pp. 49–51, 2020.

[35] D. Premraj, K. Suresh, J. Palanivel, and K. Thamilmaran, "Dynamic bifurcation and strange nonchaos in a two-frequency parametrically driven nonlinear oscillator," *Communications in Nonlinear Science and Numerical Simulation*, vol. 50, pp. 103–114, 2017.

[36] D. Premraj, K. Suresh, T. Banerjee, and K. Thamilmaran, "Bifurcation delay in a network of locally coupled slow-fast systems," *Physical Review E*, vol. 98, no. 2, Article ID 022206, 2018.

[37] D. Premraj, K. Suresh, and K. Thamilmaran, "Effect of processing delay on bifurcation delay in a network of slow-fast oscillators," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 29, no. 12, Article ID 123127, 2019.

[38] J. Palanivel, K. Suresh, D. Premraj, and K. Thamilmaran, "Effect of fractional-order, time-delay and noisy parameter on slow-passage phenomenon in a nonlinear oscillator," *Chaos, Solitons & Fractals*, vol. 106, pp. 35–43, 2018.

[39] B. Ermentrout, "Simulating, analyzing, and animating dynamical systems," *Software, environments, and tools*, vol. 14, 2002.

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Research Article

Effects of Economic Policy Uncertainty on the Investment Behavior of Venture Capital Institutions: Evidence from China

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Venture capital (VC) has played an important financial supplementary role in the development of high-tech enterprises. With the intensification of economic policy uncertainty, VC investment behavior has been affected to a certain extent. Under the framework of the impact of economic policy uncertainty (EPU) on general corporate investment behavior, this article examines the impact of EPU on the investment behavior of VC institutions from four aspects, namely, investment quantity, investment phase, investment industry, and investment region. The study finds that in China, EPU has a good news effect, and its intensification can boost the investment quantity of VC institutions and stimulate institutions to choose more specialized investment strategies in terms of investment phase, investment industry, and investment region. The impact of EPU on the investment behavior of VC institutions changes with the investment state of the institutions. The larger the investment quantity of the VC institutions, the greater the promotion effect. VC institutions with a higher degree of investment concentration will pay more attention to specialized investment strategies.

1. Introduction

China's economy is at an important turning point from high-speed development to high-quality development. In terms of the development mode, structure optimization, and power transformation, China is facing difficult tasks. As the most important driving force for economic growth, enterprises have received continuous concern and attention from academia. As one of the main sources of the enterprise growth chain, venture capital (VC) institutions have always been known as industrial incubators. Since their establishment, they have provided important growth conditions for enterprises abandoned by traditional financial institutions [1]. Until now, at least 50% of small and medium-sized high-tech enterprises in the United States have completed the achievement of transformation with support from VC investment. With the continuous improvement of the macro environment and the continuous growth of entrepreneurship and innovation opportunities, China's VC investment has also entered a golden period of development. The reasons can be summarized into two points. First, at the institutional level, VC investment is considered to be the most suitable financing channel for the development of high-tech industries [2]. Against the background of supply-side structural reform, VC investment has received strong support from the country. For early-stage high-tech enterprises especially, the driving force of VC investment cannot be underestimated. In recent years, with the help of VC investment, well-known Chinese enterprises such as Alibaba, JD.com, and Meituan have become giants. Second, once successfully withdrawn from the invested enterprise, the VC institution can obtain huge returns, which attract a large amount of capital investment. Especially since the development of mature overseas funds such as Intel Capital, IDG Venture Capital, and Walden Fund, a large number of outstanding VC institutions such as Shenzhen Venture Capital, Sequoia China, and Golden Sand Venture Capital has emerged in China. In 2018, nearly 10,000 VC investment events took place in China, involving an amount of US$70.5 billion, which put China in a leading position in the world in this regard.

To maintain the health and momentum of the follow-up development of China's VC investment, we must have a deep understanding of various risks and opportunities that

VC institutions may face. VC institutions are usually affected by four factors: technology, operations, markets, and policy [3]. As a socialist country, China's macroeconomic policy not only directly guides the decision-making of various economic entities but also determines the behavior environment of various entities, so it is the most influential factor in the VC market [4]. At present, China is in a stage of economic transformation and economic policies show obvious uncertainty [5]. The government faces uncertainties in facing the new environment, applying new thoughts, and making new decisions. Economic entities also face uncertainties in understanding new policies, learning new directions, and adapting to the new environment [6]. The introduction of the examination system and the approval system, the IPO suspension due to policy adjustments, and the restrictions on investment industries and fields have constantly overturned the original decision and disrupted the original plan. With the deepening of economic transformation, economic policy uncertainty (EPU) has generated unprecedented decision-making challenges for China's VC entities in terms of operations, markets, and policy [7].

As important investment entities in the financial market, VC institutions have business priorities, operational modes, and organizational characteristics different from those of general enterprises. For general enterprises, the impact of EPU on investment decisions is mainly reflected in reducing the quantity of investments [8], increasing innovation investments [9], upgrading service investments [10], and other behaviors. For VC institutions, this impact is mainly reflected in three classic investment behaviors: the investment phase, investment industry, and investment region [11, 12]. Therefore, the connotation of the investment behavior of VC institutions, the impact of EPU on the investment behavior of VC institutions, and the changes of the impact under different conditions become the main research questions of this study. Using the EPU index compiled by Steven et al., this article attempts to establish a two-way fixed effects model to verify the impact of EPU on the investment behavior of VC institutions. On this basis, this article further uses the quantile regression model to examine the changes in the impact of EPU on the investment behavior of VC institutions at different investment behavior levels. The results show that EPU is both a challenge and an opportunity for VC institutions, and these two characteristics change with the investment state of VC institutions. The key contributions of this study are summarized as follows:

(i) This study does not focus on the gains and losses of a single economic policy in terms of describing the macro investment environment but takes the EPU index as a representative, explores the overall impact of macroeconomic policies on VC institutions, and enriches the research on the impact of the macro investment environment on the investment behavior of micro entities.

(ii) In terms of summarizing the investment behavior of VC institutions, this study considers both the similarities and the differences between VC institutions and general enterprises, adds the variable of investment quantity, and summarizes the investment behavior of VC institutions from a four-dimensional perspective, which broadens the idea for further in-depth studies.

(iii) This study abandons the preference for the impact on VC investment performance and examines the impact of EPU on the upstream performance from the perspective of the investment behavior of VC institutions. Through longitudinal analysis under different levels of investment behavior, this study also finds that the impact of EPU on the investment behavior of VC institutions changes with the investment state of institutions and broadens the research on the interaction between EPU and the investment behavior of VC institutions.

2. Literature Review and Research Hypotheses

Since the concept of EPU emerged in the 1980s, its impact on investment at the macro and micro levels has always been a hot topic in academic and practical fields. However, macro studies mostly regard investment as one of the channels, through which EPU affects the final economic growth, and argue that EPU can cause a decline in the overall economic growth of a country by inhibiting investment [13, 14]. Micro studies mostly regard general enterprises as the research subject and explore the impact on the corporate cash holding strategy [15], investment structure strategy [16], board network strategy [17], and other investment behaviors from the perspectives of influence direction [18] and influence channel [19]. Currently, few studies link EPU with VC institutions. Therefore, considering that VC institutions are a special kind of enterprise, their investment behaviors have certain commonalities with general enterprises [20]. This article mainly uses the three mainstream theories for general corporate investment: the option theory, financial friction theory, and information asymmetry theory, to propose the hypotheses about the impact of EPU on VC institutions.

From the perspective of options, investment can be either real options or call options, and the impact of EPU on investment is not uniform. On the one hand, the waiting option theory, supported by Bernanke, McDonald and Siegel, and Gulen and Ion, emphasizes the bad news effect of EPU, arguing that investment is a real option on future cash flows [8, 21, 22]. For this theory, the core assumption is that investment is frictional and contains all kinds of imperceptible adjustment costs, the most important of which is the irreversibility of investment. Investment irreversibility means that the firm cannot sell the equipment at a price equal to or higher than the initial investment to recover the capital. This can be caused either by the lack of the secondary trading market or by the information asymmetry between buyers and sellers in secondary transactions. What is clear is that the degree of irreversibility varies across capital products. Generally, the more specialized the investment product, the higher the degree of investment irreversibility [23]. When the degree of irreversibility in venture capital is high, the institution can obtain the value of the waiting

option by waiting. Thus, by increasing investment frictions, EPU raises the marginal cost of investment, which increases the value of options [24]. The increase in the value of the option in turn prompts the institution to wait for a more suitable time to invest subsequently, which ultimately results in an investment deceleration effect [18, 25]. Pindyck demonstrates this with a theoretical model and concludes that it is the cost associated with adjustment that is the key to investment being affected by EPU [26]. Dixit and Pindyck further confirm the suitability of real options theory to reality by comparing net present value theory with real options theory [27].

On the other hand, the growth option effect, supported by scholars such as Myers, Bloom, and Segal et al., mainly emphasizes the good news effect of EPU [28–30]. In this theory, the overall value of the firm includes both the current value of assets and the contingent value given by investment opportunities. The investment opportunity is a call option [28], which is held by the firm itself. Under asymmetric benefit and cost mechanisms, EPU has the opportunity to drive upward the value of call options. Specifically, the cost of a firm's investment generally fluctuates only slightly in response to EPU, but the value of the potential return on investment can fluctuate significantly in response to EPU. As a result, firms would seize every opportunity to invest more in order to capture the market by making small costs [29]. Especially in a competitive environment, firms can only expand their market dominance by continuously investing, when EPU enhances the possibility of firms to capture the market through investment and increases the value of call options [31]. In addition, when investment is not completely irreversible, institutions are able to adjust the scale of investment in response to changes in the environment, and institutional managers are more likely to view investment opportunities as call options with limited losses and unlimited gains [30]. Although in the short run, the assumption of investment reversibility goes against reality to a certain extent [26], in the long run, institutions are indeed able to make decisions to a greater extent in response to changes in market information [29]. Therefore, the positive impact of EPU on investment always has its realistic rationality in either direction.

From the perspective of financial friction, VC investment can be reduced due to the financing obstacles caused by EPU. It is because there are frictions in the financial market that EPU can amplify the cost of financing. If there were no frictions in the financing market, the impact of corporate financing costs on investment decisions would be greatly diminished, when EPU is unable to exploit financing costs, significantly reducing the disincentive to invest [32]. In fact, however, frictions are ubiquitous [33]. In real markets, firms are tied to a variety of financing problems and even have to pay much higher external funding than their internal costs [34]. Especially in an environment of EPU, firms have to face increased financing costs, whether they finance internally or externally. For internal financing, as stated in the precautionary motivation theory supported by Carroll and Samwick [35], the risk represented by EPU can force enterprises to give up part of their investments to ensure internal cash flow [15, 36]. For external financing, as stated in the risk premium theory of Gilchrist et al. [32], when the capital investors of investment institutions perceive the potential risks from EPU, their expected returns increase as uncertainty rises, thereby increasing the financial burden on VC institutions [37]. Therefore, financial friction constrains the free capital of enterprises, and based on the option theory, it amplifies the inhibiting effect of EPU on VC investment.

From the perspective of information asymmetry, EPU has a positive effect on the level of VC investment. The main players in VC can be divided into three parties: individual investors, venture capitalists, and startup entrepreneurs. According to principal-agent theory, venture capitalists take advantage of the asymmetric information environment to establish a two-tier principal-agent relationship between startups and individual investors [38]. In an asymmetric information environment, where EPU increases information bias among agents, startups tend to change key information to amplify expected returns [39]. When expected returns increase, venture capitalists are more likely to focus on the potential opportunities and profits from uncertainty and less on the underlying risks and losses, thus magnifying risk-seeking characteristics [40–42]. Moreover, EPU implies increased policy ambiguity for venture capitalists, which leads to an increase in investors' investment sensitivity, relying more on their own technical judgment than on following the policy pace. Investors are more likely to notice investment details that they would not have noticed if the policy was clear, and thus they are able to increase investment efficiency [43]. In addition, although information asymmetry can also lead to insufficient information about investments in the market, which makes it difficult for venture capitalists to grasp the current investments [23], VCs are usually able to compensate for this through co-investment strategies. As evidenced by Ter Wal et al., the less experience VCs have accumulated in a particular field, the more likely they are to make co-investments [44].

Based on the above three perspectives, this article proposes a pair of competing hypotheses:

> *H1a*. EPU has an inhibiting effect on the investment quantity of venture capital institutions. In other words, EPU has a bad news effect and increases financial friction, thereby inhibiting the investment quantity of venture capital.
>
> *H1b*. EPU has the effect of promoting the investment quantity of venture capital institutions. In other words, EPU has a good news effect and blurs the situation of information asymmetry, thereby stimulating the investment quantity of venture capital.

In addition to the commonalities, there are many differences between VC institutions and general enterprises, which lead to the unique investment strategies of VC institutions. In general, the investment strategies of VC institutions can be divided into specialization strategies and diversification strategies, and the differences between the two are mainly reflected in three aspects: the investment

phase, investment industry, and investment region [11]. Specialized strategy means that investment institutions make centralized treatment in the project intervention stage, investment industry, and investment area. Diversified investment strategy means that investment institutions make decentralized treatment in the project intervention stage, investment industry, and investment region. According to the characteristics of these two strategies, we can analyze them from two perspectives such as risk and opportunity, and the benefits and costs of information.

From the perspective of risk and opportunity, EPU may be viewed as either a risk, which leads VCs to choose specialized investment strategies, or as an opportunity, which leads them to choose diversified investment strategies. When EPU is regarded as a risk, VCs tend to think about survival, i.e., how to use their limited resources to control their exposure to risky shocks. Generally, the specialization strategy implies that the VCs have a considerable degree of professional understanding and experience in the existing investment stage, industry, and region. Therefore, the use of specialized strategies can help VCs reduce the cost of information collection, decision-making, and behavior and maximize the integration of resources, so as to achieve the purpose of avoiding risks [45, 46]. When EPU is seen as an opportunity, VCs usually tend to consider the expansion problem, i.e., how to seize the opportunity to compete for the market when the situation is uncertain. In general, diversification strategy implies that VCs need to proactively reach out to unexplored investment stages, industries, and regional projects based on their original investment areas. Therefore, the use of diversification strategy can guide VCs to form their own resource networks in multiple investment stages, investment industries, and investment regions, so as to achieve resource sharing and even provide certain synergistic effects, laying the foundation for VCs' expansion [47, 48].

From the perspective of benefits and costs of information, the question about whether EPU leads VCs to choose diversification or specialization strategies is also unclear. On the one hand, when a VC is in an environment of high EPU, it may adopt a diversified investment strategy out of the idea of information sharing. Diversification strategy can drive VCs to reach information outside the original investment circle, thus creating a sharing effect between the new information and the original information, bringing more social interaction, connection, and value to the VCs, and mitigating some of the negative effects of information asymmetry [48, 49]. On the other hand, in an environment of EPU, information is a critical factor in seizing market opportunities, and VCs, realizing the importance of reducing the time and material investment required to collect information, may focus more on leveraging their own information advantages in the original investment stage, investment industry, and investment region. This will reduce the exploration of new fields and the possibility of investment failure [50, 51]. Based on the above, this study proposes the following hypotheses:

H2a. EPU can guide venture capital institutions to use specialized investment strategies in terms of investment phase, industry, and region.

H2b. EPU can guide venture capital institutions to use diversified investment strategies in terms of investment phase, industry, and region.

3. Model Setting and Data Description

3.1. Variable Selection

3.1.1. Measurement of EPU. This article uses a mainland newspaper-based index compiled by Steven et al. to measure China's EPU. This index is based on the compilation method of the BBD index [13] and uses two newspapers in mainland China, *People's Daily* and *Guangming Daily*, to quantify concepts related to uncertainty in China since October 1949. To better match the sample data, this article standardized the EPU data and used the weighted geometric mean to convert the monthly data of China's EPU index into the annual EPU index [52], that is

$$\mathrm{EPU}_t = \sqrt[12]{\mathrm{MEPU}_{t1} \times \mathrm{MEPU}_{t2} \times \ldots \times \mathrm{MEPU}_{t12}}, \quad (1)$$

where EPU is the annual EPU index and MEPU is the monthly EPU index of the corresponding year.

3.1.2. Investment Behavior of Venture Capital Institutions. Considering the homogeneity of VC institutions and general enterprises, this study regards investment quantity, which is the most intuitive investment behavior of general enterprises, as one of the most intuitive and main investment behaviors of VC institutions. Specifically, this study uses the total investment amount of VC institutions in the observation year to measure the investment quantity of VC institutions [8].

Considering the differences between VC institutions and general enterprises, after Gupta and Sapienza studied the investment phase, investment industry, and investment region as the main VC strategy [11], this study also conducts research on the behavior of VC investment on this basis. Specifically, this study uses the HHI (Herfindahl–Hirschman index) to describe the investment situation of VC institutions in various phases, industries, and regions. The HHI is a representative indicator reflecting the degree of concentration and can measure the investment concentration degree of VC institutions in various investment phases, investment industries, and investment regions:

$$HHI_a = \sum \left(\frac{\text{Number of } a \text{ events for investement class } i}{\text{Total number of investement events}} \right)^2, \quad (2)$$

where the phases of enterprise development are divided into the seed stage, startup stage, expansion stage, and maturity stage. The industrial classification refers to the industrial classification for national economic activities, and the regional classification refers to the first-level administrative divisions.

3.1.3. Control Variables. In order to control the factors that affect the investment behavior and try to avoid the deviation caused by omitted variables, this study adds some control

Table 1: Variable names and meanings.

Type of variable	Variable name	Variable description
Explained variable	Investment quantity (quantity)	The logarithm of the total investment expenditure of the venture capital institution in observation year
	Investment phase (phase)	HHI of the investment phase of the venture capital institution in observation year
	Investment industry (industry)	HHI of the investment industry of the venture capital institution in observation year
	Investment region (region)	HHI of the investment region of the venture capital institution in observation year
Explanatory variable	Economic policy uncertainty (EPU)	Annualized 12-month economic policy uncertainty index
Control variable	Micro control variable	
	Location of fund (LOC)	LOC is 1 if the location of the fund is domestic, and 0 otherwise
	Institution age (AGE)	Years of the establishment of the venture capital institution by the sample observation year
	Cumulative number of investment events (INV)	Number of investments, in which the venture capital institution participated before the sample observation year
	Number of successful IPO (IPO)	Number of successful IPO withdrawals of the venture capital institution before the sample observation year
	Size of venture capital institution (SIZE)	The natural logarithm of the average value of funds managed by venture capital investment during the sample period
	Macro control variable	
	Economic growth rate (GDP)	GDP year-on-year growth rate in the sample observation year
	Index of consumer sentiment (ICS)	Index of consumer sentiment in the sample observation year
	Stock returns (STOCK)	The average growth rate of the Shanghai and Shenzhen composite indices, multiplied by 100
	Market issuance (MARKET)	Number of domestic A-share newly listed companies in the sample observation year
	Global policy uncertainty (GPU)	Annualized 12-month global policy uncertainty index

variables when analyzing the investment behavior of venture capital institutions. Drawing on relevant studies by Kaplan and Schoar and Lutz et al., the control variables used in this study include both individual characteristics of VCs and the characteristics of the macro environment (Table 1) [53, 54].

The individual characteristics of VCs are used to describe the investment status of individual institutions. In this study, we use the nature of ownership (LOC), the age of the institution (AGE), and the scale of venture capital institutions (SIZE) to measure the institutional attributes of venture capital institutions, and the cumulative number of investment events (INV) and investment success (IPO) to measure the investment experience of venture capital institutions.

The macro-environmental characteristics are used to describe the investment background of venture capital institutions. This study uses economic growth rate (GDP) and consumer confidence index (ICS) to measure the overall domestic macro background, stock returns (STOCK), and market issuance (MARKET) to measure the sentiment of the domestic investment market, and global uncertainty (GPU) to measure the investment pressure brought by the international environment.

3.2. Model Construction. Based on the characteristics of unbalanced panel data in this article, considering that VC institutions are affected by unobservable individual differences and the macro environment when making decisions, this study constructs the following two-way fixed effect model to verify the above hypotheses:

$$Y_{\mathrm{it}}^{n} = \beta_0 + \beta_1 \mathrm{EPU}_{\mathrm{it}} + \sum_{m=2}^{10} \beta_m \mathrm{CONTROL}_{m,\mathrm{it}} + \mu_i + \sum \mathrm{year} + \varepsilon_{\mathrm{it}}, \tag{3}$$

where Y_{it}^{n} refers to the four dimensions of investment behavior, specifically investment quantity ($\mathrm{Quantity}_{\mathrm{it}}$), investment phase ($\mathrm{Phase}_{\mathrm{it}}$), investment industry ($\mathrm{Industry}_{\mathrm{it}}$), and investment region ($\mathrm{Region}_{\mathrm{it}}$), μ_i is the unobservable individual effect, $\sum \mathrm{year}$ is the time effect, and $\varepsilon_{\mathrm{it}}$ is the time-varying disturbance term of an individual.

This study selected the annual data of China's VC institutions from 1997 to 2019 as the research sample. Before the empirical analysis, we sorted out the VC events that occurred from 1997 to 2019, excluded the data without investment quantity, and obtained a total of 6,561 investment events from 1,666 VC institutions. We excluded the data without investment phase, investment region, and investment industry and obtained a total of 5,156 investment events from 1,287 VC institutions. The VC investment data were selected from the Zero2IPO database, and the economic policy uncertainty was selected from the EPU1 index jointly published by Stanford University and the University of Chicago.

3.3. Data Description. Observing the trend of China's EPU (Figure 1), we can find that the EPU in China has the characteristics of periodic fluctuations. Before 2007, there were no major political and economic events in China, so the level of EPU in China was stable and relatively low. From

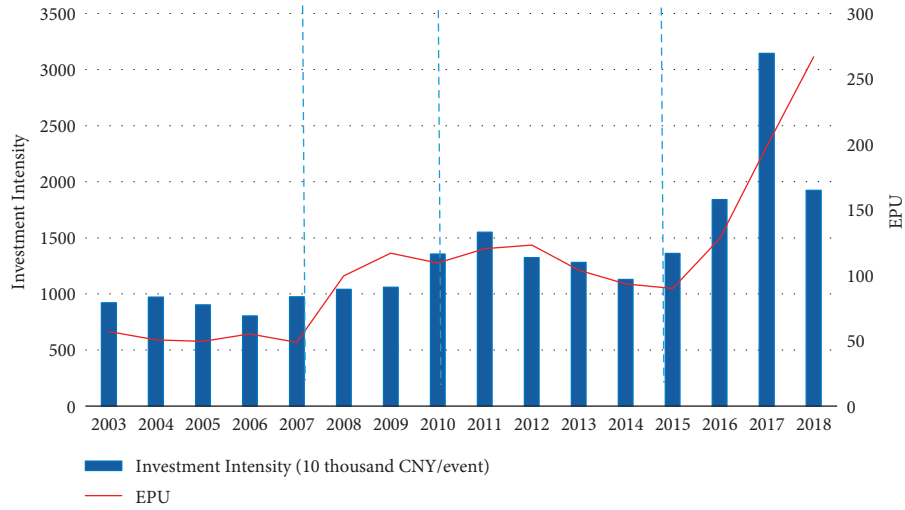

Figure 1: EPU and the quantity of venture capital investment in China.

2007 to 2009, the level and fluctuation of EPU in China were significantly higher than during the first stage. This was mainly due to the global financial crisis in 2008, and the Chinese government frequently adjusted economic policies to save the market. In the first half of 2010 to 2014, events such as the change in national leaders and the European debt crisis occurred one after another, so a high level of EPU was maintained. In the second half, no major events occurred, so there was a gradual downward trend in the level of EPU in China. In 2015 and after, events such as China's economic new normal, the Sino-US trade friction, and the global COVID-19 pandemic, occurred one after another; thus, the EPU in China began to grow rapidly again with violent fluctuations.

Considering the fluctuating trend of investment intensity in China, we find that the VC investment intensity and EPU are almost synchronized. This means that there are certain positive correlations between EPU and concentration of the VC investment.

The investment quantity, investment phase, investment industry, and investment region, as the reflections of willingness to invest in VC, also show the following characteristics according to the corresponding statistical descriptions (Table 2).

In terms of investment quantity, China's VC investment has great volatility, which is not only reflected in the whole industry but also reflected in individual institutions. In terms of the whole industry, the overall standard deviation of quantity is 1.965. Compared to the indicators of other investment behaviors, it is evident that the total investment of different institutions in the same year is quite different. On this basis, this study finds that the overall sample mean of quantity is 1.473, which is far from the overall maximum value of 11.131 and the minimum value of −6.908. Therefore, this study speculates that the investment of institutions themselves in different years may also have a large gap. Thus, this study takes the overall sample mean of quantity 1.473 as the dividing line and randomly samples 10% of the institutions with larger and smaller quantity values respectively.

Table 2: Descriptive statistics for each variable.

Variable	Mean	Std. dev.	Min	Max
Quantity	1.473	1.965	−6.908	11.131
Phase	0.766	0.271	0.250	1.000
Industry	0.662	0.346	0.027	1.000
Region	0.744	0.312	0.048	1.000
EPU	1.341	0.167	1.051	1.773
LOC	0.797	0.402	0.000	1.000
SIZE	8902.614	28813.510	0.001	347175.000
AGE	20.157	7.265	0.000	112.000
IPO	4.016	13.078	0.000	239.000
INV	28.599	74.335	1.000	1240.000
GDP	0.083	0.019	0.060	0.142
ICS	1.390	0.233	1.135	1.931
STOCK	0.093	0.432	−0.644	1.315
MARKET	3939.752	2583.941	18.000	7509.000
GPU	1.201	0.125	1.040	1.545

Through preliminary observation of the scatter plot of the total investment of the sample institutions in different years, this study finds that the total investment of a single institution in different years also has a large difference.

In terms of investment strategies, China's VC institutions show a high degree of investment concentration in phases, industries, and regions. The HHI has always been considered by the U.S. Department of Justice as a good indicator of industrial concentration. It is generally believed that when the HHI of an industry is greater than 0.3, the industry is considered to be in a state of high oligopoly. In this study, the overall mean values of phase, industry, and region are 0.766, 0.662, and 0.744, respectively, which means that the HHI of venture capital institutions in terms of investment stage, investment industry, and investment region is far higher than 0.3. Therefore, it can be considered that the investment concentration of venture capital institutions in industries, regions, and stages is relatively high; that is, China's venture capital industry shows certain specialized investment characteristics.

4. Empirical Results

4.1. Estimation Results for Benchmark Equation. Incorporating the above descriptive statistical results and the observation on each variable, we first winsorized the variables to avoid the influence of abnormal data on the research results. Based on this, we conducted regression analysis on the dependent variables, including $Quantity_{it}$, $Phase_{it}$, $Industry_{it}$ and $Region_{it}$. The results are listed in Table 3. The Hausman test results of the four equations are all significant at the 1% level. It can be found that the relationship between EPU and the investment behavior of VC institutions is adaptable to a fixed effects model.

At the same time, in the equation of investment quantity, the coefficient of EPU is 2.480, which is significant at the 5% level. In the equations of investment phase, investment industry, and investment region, the coefficients of EPU are 1.666, 2.010, and 1.778, respectively, all of which are significant at the 1% level. Therefore, we believe that EPU not only stimulates the investment quantity of VC institutions but also boosts the investment concentration of VC institutions in investment phases, investment industries, and investment regions.

4.2. Discussion on Endogeneity. In terms of endogeneity, this article considers both macro and micro factors. From the micro perspective, the explanatory variable in this article is the EPU at the macro level, and the explained variable is the investment behavior of VC institutions at the micro level. The influence of micro individuals on macro indicators is almost negligible, so the endogeneity problem caused by bidirectional causality is alleviated to a large extent. In addition, according to Gulen and Ion, when studying the impact of EPU on corporate investment, the most important problem was the endogeneity caused by the missing variable of corporate future investment opportunities [8]. In this study, the indicators, including the institutional capital, the cumulative number of investment events, and the number of successful investments, are introduced into the four equations. These indicators basically summarize the investment opportunities at the individual institutional level. Therefore, when considering the instrumental variable, we focus on the distortion of results caused by the absence of macro investment opportunities.

In the original model, the GDP growth rate depicts the macro development of China in the current year relative to that in the previous year. The index of consumer sentiment predicts consumers' plans for future consumption life from the perspective of consumption. The stock returns and market issuance describe the current level of investment in the domestic market from the investment perspective. The global policy uncertainty is the nonlocal feature of some VC investments, including the overall uncertain environment in domestic and foreign countries. Among the five indicators, GDP growth rate and the index of consumer sentiment involve the prediction of the future market to a certain extent. However, the ability of GDP growth rate to predict the future is not strong, and VC institutions do not directly face consumers, resulting in a slight lag in the ability of these two indicators to comprehensively reflect future investment. Therefore, in satisfying the main conditions of the instrumental variable, this study selects the macroeconomic performance indicator-leading indicator (MacroPI) as an instrumental variable in the regression model. The rationality of this instrumental variable can be demonstrated separately in the theoretical and empirical models.

In theory, MacroPI can be used as an instrumental variable for EPU for two reasons. On the one hand, MacroPI is absolutely exogenous and closely related to EPU. Based on the survey of entrepreneurs, MacroPI integrates the entrepreneurs' judgments on the operation of enterprises and the operation of the macroeconomy and objectively reflects the development trend of the future economy from the enterprise level. Both MacroPI and EPU are macroeconomic indicators, and their degree of correlation is significant. On the other hand, MacroPI mainly affects the investment behavior of VC institutions by affecting EPU. MacroPI is regarded as a macro barometer and is a reference for many economic, fiscal, and monetary policies. Therefore, it must have a significant impact on China's EPU, thus affecting the investment behavior of VC institutions.

Empirically, this study tested the rationality of the instrumental variable in three steps:

First, we conducted the Hausman test and the Davidson–MacKinnon test on the four dimensions of the investment behavior of VC institutions. The results showed that the endogeneities of investment region, investment phase, and investment industry were evident in the two tests. Although the endogeneity of investment quantity was not evident in the Hausman test, its endogeneity was detected in the supplementary Davidson–MacKinnon test (Table 4). Therefore, in order to avoid the interference of endogeneity on the results as much as possible, our analysis model for the four dimensions would include the instrumental variable, which is the macroeconomic performance indicator. Then, based on the ideas of Acemoglu et al. and Miguel et al. [55, 56], we put MacroPI into four equations to investigate its rationality. Table 4 lists that MacroPI has a significant positive effect on the investment quantity of VC institutions, but after adding EPU to the regression model, the impact of MacroPI on the investment quantity of VC institutions is less significant, and the significance of EPU is enhanced. This shows that the impact of MacroPI on the investment quantity of VC institutions is covered by EPU. In other words, the impact of MacroPI on the investment quantity of VC institutions in China is mainly due to EPU. Like the investment quantity, MacroPI also has a significant positive effect on the specialization level of VC institutions in investment phases, industries, and regions. Moreover, after EPU was added to the regression model, the impact of MacroPI on the specialization level of VC institutions in investment phases, industries, and regions is no longer significant. This shows that the impact of MacroPI on the specialization level of VC institutions in investment phases, industries, and regions can be largely covered by EPU. In other words, the impact of MacroPI on the specialization level of VC institutions in China is mainly due to EPU.

Table 3: Estimation results of benchmark equations.

	Equation (1) Quantity	Equation (2) Phase	Equation (3) Industry	Equation (4) Region
EPU	2.480** (1.083)	1.666*** (0.166)	2.010*** (0.216)	1.778*** (0.205)
LOC	−2.106*** (0.088)	−0.133*** (0.017)	−0.257*** (0.023)	−0.229*** (0.019)
SIZE	−0.002*** (9.75e − 05)	−0.001*** (0.001)	−0.001*** (0.001)	−0.001** (0.001)
AGE	−0.037** (0.018)	0.007** (0.003)	0.010** (0.004)	0.004 (0.013)
IPO	0.044*** (0.014	0.003 (0.003)	0.008** (0.003)	0.001 (0.002)
INV	−0.023*** (0.002)	−0.003*** (0.001)	−0.004*** (0.001)	−0.003*** (0.001)
GDP	30.045 (24.922)	28.061 (4.241)	38.2124*** (5.211)	31.716*** (4.887)
ICS	−3.092** (1.481)	0.905*** (0.203)	1.052*** (0.271)	0.696*** (0.263)
STOCK	1.302*** (0.373)	0.098* (0.055)	0.167** (0.070)	0.231*** (0.068)
MARKET	0.001** (0.001)	−9.04e − 06 (0.001)	−5.87e − 06 (0.001)	0.001 (0.001)
GPU	7.390* (3.958)	−2.640*** (0.542)	−3.249*** (0.717)	−2.430*** (0.697)
_cons	−8.641*** (2.563)	−1.640*** (0.552)	−2.464*** (0.653)	−2.089*** (0.585)
Individual	Control	Control	Control	Control
Year	Control	Control	Control	Control
N	6561	5156	5156	5156
Hausman	55.25***	104.81***	54.50***	128.56***
P value	0.0000	0.0000	0.0000	0.0000

Note. *, **, and ***represent the significance at the 10%, 5%, and 1% levels, respectively. The robust standard errors are shown in parentheses. Control represents the control for individual effects and time effects. The coefficients of the variables LOC and SIZE are estimated using LSDV (least squares dummy variable).

Finally, we used two-stage least squares (2SLS) to bring instrumental variables into the test to address endogeneity, following the lines of Acemoglu et al. and Miguel et al. [55, 56]. In the first stage, we used EPU as the dependent variable and MacroPI as the independent variable, kept the control variables unchanged to perform the regression analysis, and obtained the results listed in Table 5. It can be found that the impact of MacroPI on EPU is significant at the 1% level in the four-dimensional model, and the robust F values of the four regression models are all much greater than 10. Therefore, the possibility of the weak instrumental variable is rejected.

In the second stage, we used the four dimensions of the investment behavior of VC institutions as the dependent variables, used the EPU1 obtained from the first-stage fitting as the independent variable, kept the control variables unchanged to perform the regression analysis, and obtained the results listed in Table 5. Compared to the benchmark test results, it can be found that the impacts of EPU on the four dimensions of the investment behavior of VC institutions change in different magnitudes after the addition of MacroPI. Yet overall, the direction and significance of the impacts remain unchanged, which proves that after excluding the endogeneity caused by missing variables, the conclusions of this study are still robust.

After solving the endogeneity problem, it can be found that on the one hand, EPU does promote the investment quantity of VC institutions, which is consistent with the inference of previous descriptive statistics. 2SLS regression is performed on equation (1). The estimated coefficient of EPU is 3.343, which is significant at the 1% level. Compared to the benchmark regression, the promotion effect is slightly improved. This effectively confirms hypothesis H1b of this study. It means that when EPU changes, VC institutions are more vulnerable to positive factors such as call options and information asymmetry. Based on the first-stage estimation results of the instrumental variable (Table 5), we find that before EPU promotes the investment quantity of VC institutions, the macroeconomic performance indicator also has a positive effect on EPU. This also means that the macroeconomic performance indicator also promotes the great influence of positive factors such as call options. Meanwhile, EPU also has a positive stimulating effect on the concentration degree of VC institutions in investment phases, industries, and regions. 2SLS estimation was performed on equations (2) to (4). The estimated coefficients of EPU are 0.771, 0.876, and 0.905, respectively, all of which are significant at the 1% level. Compared to the benchmark regression, all stimulation effects decrease significantly. However, it still confirms hypothesis H2a of this study, which states that EPU can stimulate VC institutions to use specialized investment strategies.

In general, EPU can prompt China's VC institutions to increase investment in areas already covered and shows that the uncertainty is both an opportunity and a challenge. To avoid the unlimited risk brought by the challenge, VC institutions tend to use specialized investment strategies. To seize the opportunity of increasing market share brought by the opportunity, VC institutions tend to increase investment in areas already covered.

4.3. Robustness Test

4.3.1. Sample Period Adjustments. This study uses data from 1997 to 2019 to study the impact of EPU on the investment behavior of VC institutions. However, most of the existing research on VC investment began in 2005. According to the textbook *Equity Investment Fund*, China's equity investment before 2005 was basically in the exploratory and initial stage. There were few market participants and VC events, and investment behavior was irregular. Therefore, to avoid

Table 4: Rationality test for the MacroPI instrumental variable.

	Quantity				Phase	
EPU	2.480** (1.083)		9.625*** (3.734)	1.666*** (0.166)		1.677*** (0.382)
MacroPI		3.042*** (1.329)	−8.766* (5.18)		1.381*** (0.138)	−0.010 (0.298)
Individual	Control	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control	Control
N	6561	6561	6561	5156	5156	5156
Hausman test		0.6397			0.000	
Davidson–MacKinnon test		0.0749			2.4e−06	
	Industry				Region	
EPU	2.010*** (0.216)		1.858*** (0.492)	1.778*** (0.205)		2.343*** (0.463)
MacroPI		1.667*** (0.179)	0.126 (0.418)		1.474*** (0.170)	−0.468 (0.421)
Individual	Control	Control	Control	Control	Control	Control
Year	Control	Control	Control	Control	Control	Control
N	5156	5156	5156	5156	5156	5156
Hausman test		0.000			0.000	
Davidson–MacKinnon test		$7.3e-08$			$2.0e-09$	

Note. *, **, and ***represent the significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Comparison between the estimation results of the instrumental variable in two-stage least squares (2SLS) and the benchmark results.

		The first-stage regression		
		EPU1		
MacroPI		0.181*** (0.005)		
F value	1493.52	1122.34	1122.34	1122.34
	The second-stage regression and the benchmark regression			
	Quantity	Phase	Industry	Region
EPU1 (2SLS regression)	3.343*** (0.718)	0.771*** (0.140)	0.876*** (0.174)	0.905*** (0.147)
EPU (benchmark regression)	2.480** (1.083)	1.666*** (0.166)	2.010*** (0.216)	1.778*** (0.205)
Individual	Control	Control	Control	Control
Year	Control	Control	Control	Control
N	6032	4728	4728	4728

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

irregularities from interfering with the empirical results, this article adjusted the sample period from 2005 to 2019 and estimated again. In addition, most of the existing research on EPU agreed that the 2008 financial crisis caused global EPU to rise to a new height. Therefore, we adjusted the sample period from 2008 to 2019 and estimated again. The two estimation results are listed in Table 6. We can find that the results of the two sample period adjustments are all significant at the 1% level and the results are similar to the empirical results of the full sample, indicating that the results of this study are robust.

4.3.2. Replacement of the EPU Measurement Method. This study considers replacing the main proxy variables to demonstrate the robustness of the obtained results. Currently, the measurement of annual EPU is mainly divided into two types: one is the weighted geometric mean (i.e., the annual $\mathrm{EPU}_t = \sqrt[12]{\mathrm{MEPU}_{t1} \times \mathrm{MEPU}_{t2} \times \ldots \times \mathrm{MEPU}_{t12}}$), where t represents the month), and the other is the arithmetic mean (i.e., $\mathrm{EPU}_t = \sum_{t=1}^{12} \mathrm{MEPU}_t/12$, where t represents the month). In previous paragraphs, we used the weighted geometric mean to measure EPU, so we used the arithmetic mean to process the EPU index and re-estimated the impact of EPU on the investment behavior of VC institutions. The estimation results are listed in Table 7. It can be found that the conclusions obtained after the index replacement are similar to the previous conclusions, so the conclusions obtained in this study are robust.

4.3.3. Replacement of Estimation Method. This study mainly adopts the 2SLS method to overcome the endogeneity problem. However, when heteroscedasticity exists, the two-step GMM (generalized method of moments) method can capture the heteroscedasticity information more acutely because it requires fewer assumptions and only needs to satisfy the moment conditions. Therefore, it is more effective than the 2SLS method and the obtained results are more reliable. Thus, this article uses the two-step GMM method to estimate the robustness of the whole sample, bringing MacroPI as the instrumental variable corresponding to EPU into the estimation, and the results are listed in Table 8. It can be found that the results of the two-step GMM estimation are the same as the results of 2SLS. This indicates that the sample size used in this study is large enough, and the conclusions obtained are robust and credible.

4.4. Heterogeneity Analysis. Based on the Hausman test, we find that compared to the random effects model, the two-way fixed effects model can better explain the correlation between variables. However, for panel regression, both random effects and fixed effects can only reflect a single fixed relationship and the significance level between variables. It is difficult to obtain the different effects of EPU on the investment behavior of VC institutions under different investment behaviors. Therefore, after the initial test, it is helpful to conduct further research using panel quantile regression to understand the overall impact of EPU on the investment behavior of VC institutions.

In addition, both the two-way fixed effects model and the 2SLS model are based on the least squares estimation method and examine the mean regression of the explanatory variables on the explained variables. However, it is difficult to fit the real data to the assumption of the least squares method, which may easily lead to unrepresentative conclusions and poor robustness. In this case, Koendker and Bassett [57] proposed quantile regression, which makes no specific assumptions about the sample distribution but can make the conclusion more robust. Moreover, the least squares estimation can only reveal the impact of EPU on the investment behavior variable of VC institutions at the average level, while quantile regression can specifically describe the impact of EPU on the overall conditional distribution of the investment behavior of VC institutions. This means that through quantile regression, the impact of EPU on the investment behavior of VC institutions obtained in this study will be more stable and representative.

The quantile regression model settings in this study are as follows:

$$Q_{Y_{i,t}}\left(\tau | X_{i,t}\right) = X_{i,t}'\beta(\tau). \tag{4}$$

The coefficient estimation formula is as follows:

$$\widehat{\beta}(\tau) = \min_{\beta} \sum_{t=1}^{T} \sum_{i=1}^{n} \rho_{\tau k}\left(Y_{i,t} - X_{i,t}'\beta(\tau)\right), \tag{5}$$

Table 6: Robustness test for split samples.

	Quantity	Phase	Industry	Region
EPU (2008–2019)	6.928*** (2.015)	1.909*** (0.433)	2.243*** (0.526)	2.438*** (0.462)
EPU (2005–2019)	3.710*** (0.889)	0.946*** (0.165)	1.080*** (0.204)	1.138*** (0.174)
EPU (original 2SLS regression)	3.343*** (0.718)	0.771*** (0.140)	0.876*** (0.174)	0.905*** (0.147)
Individual	Control	Control	Control	Control
Year	Control	Control	Control	Control

Note. ***represents the significance at the 1% level.

Table 7: Robustness test for EPU* index replacement.

	Quantity	Phase	Industry	Region
EPU	3.343*** (0.718)	0.771*** (0.140)	0.876*** (0.174)	0.905*** (0.147)
EPU*	15.496*** (4.315)	2.422*** (0.555)	2.750*** (0.674)	2.841*** (0.610)
Individual	Control	Control	Control	Control
Year	Control	Control	Control	Control
N	6032	4728	4728	4728

Note. ***represents the significance at the 1% level.

Table 8: Robustness test for the two-step GMM method.

	Quantity	Phase	Industry	Region
EPU (GMM estimation)	3.343*** (0.718)	0.771*** (0.140)	0.876*** (0.174)	0.905*** (0.147
EPU (2SLS regression)	3.343*** (0.718)	0.771*** (0.140)	0.876*** (0.174)	0.905*** (0.147)
Individual	Control	Control	Control	Control
Year	Control	Control	Control	Control
N	6032	4728	4728	4728
Instrumented	EPU			
Included instruments	AGE, IPO, INV, GDP, ICS, STOCK, MARKET, and GPU			
Excluded instruments	MacroPI			

Note. ***represents the significance at the 1% level.

where $\tau \in (0,1)$ is the quantile, $Y_{i,t}$ represents the observation of the four investment behavior levels of individual i in year t, $X_{i,t}$ is the sample observation of explanatory variables, $Q_{Y_{i,t}}(\tau|X_{i,t})$ is the conditional quantile of the investment behavior level $Y_{i,t}$ at the τ quantile, $\beta(\tau)$ is the coefficient of each explanatory variable affecting the investment level $Y_{i,t}$ at the τ quantile, and $\rho_{\tau k} = k(\tau - I(k<0))$ is a piecewise linear function. For the τ value, this study took a value every 0.1 quantiles for a total of nine values. Starting from 0.1, as shown in Figures 2 to 5, the solid line is the estimated coefficient of the investment behavior variable, and the upper and lower dashed lines are the boundaries of the 95% confidence interval.

Based on the panel quantile result of Quantity (Figure 2), on the one hand, EPU has a stable effect on promoting the investment quantity of VC institutions. The estimated coefficients of EPU are consistently positive from the 10th to 90th quantiles, and all coefficients are significant at the 1% level. This shows that at all levels of investment quantity, the increase in EPU can significantly stimulate the investment willingness of VC institutions, which is consistent with the previous conclusion that the influence of positive factors is greater than the influence of negative factors. On the other hand, as the investment quantity of VC institutions increases, the positive impact of EPU on the investment quantity is enhanced. In the case where the estimated coefficient of EPU is positive, the absolute value of the coefficient increases continuously from the 10th to the 90th quantile. This indicates that as the investment quantity increases, negative factors such as real options have a weaker impact than positive factors such as call options. In other words, for institutions with larger investment quantities, EPU means more opportunities. VC institutions with larger investment quantities tend to seize the opportunity of rising EPU to increase investment and expand their market share.

Based on the panel quantile results of phase, industry, and region, on the one hand, EPU has a stable effect on promoting the concentration degree of VC investment phases, industries, and regions. The estimated coefficients of EPU in the three models are consistently positive from the 10th to 90th quantiles, and all coefficients are significant at the 1% level. This indicates that under all concentration degrees in investment phases, industries, and regions, the increase in EPU can significantly stimulate VC institutions to narrow the investment scope, which is consistent with the spatial concentration theory verified by equations (2) to (4) in the preliminary test. On the other hand, as the concentration degree of VC institutions in investment phases, industries, and regions increases, the positive impact of EPU on the investment industry and region has different degrees of magnification. From Figures 3 to 5, it can be found that the EPU coefficients of the investment phase, industry, and region increase significantly from the 10th to the 90th quantile. Based on the background and strength of VC

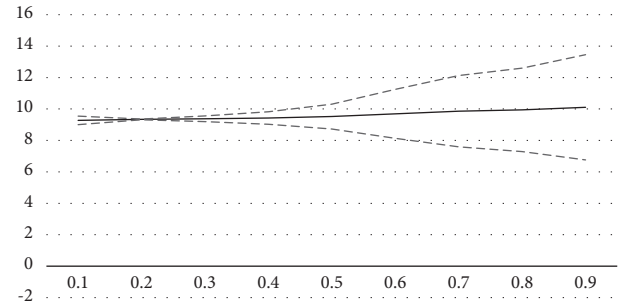

Figure 2: Quantity-EPU quantile regression result.

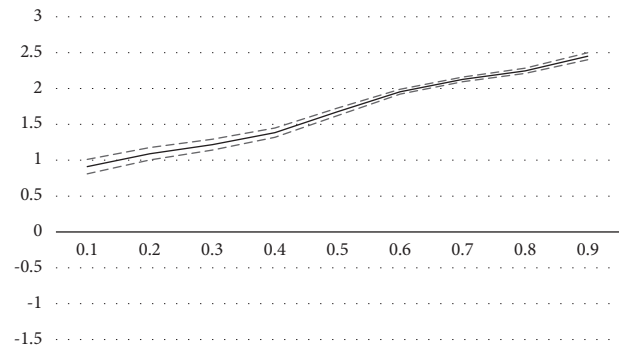

Figure 3: Phase-EPU quantile regression result.

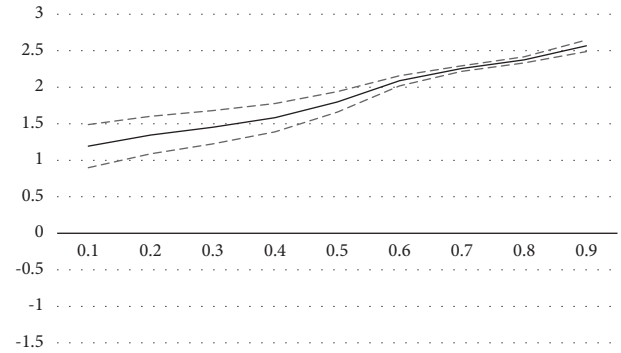

Figure 4: Industry-EPU quantile regression result.

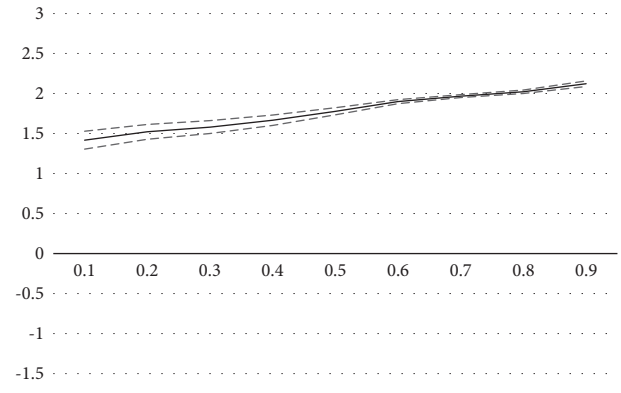

Figure 5: Region-EPU quantile regression result.

institutions, a low concentration degree in investment phases, industries, and regions indicates that the VC institution plans to expand the market. This expansion usually means higher decision-making costs. In general, institutions with an excellent investment state are more able to bear this cost. Therefore, for VC institutions with a low concentration degree in investment phases, industries, and regions, or VC institutions with an excellent investment state, the impact of EPU on changing their investment behavior is relatively weak.

5. Conclusions and Inspirations

Combining the investment behavior framework of general enterprises and the behavior characteristics of venture capital institutions, this study summarizes the connotation of investment behavior of venture capital institutions, namely, investment scale, investment stage, investment industry, and investment area. From these four aspects, this study examines the impact of EPU on the investment behavior of venture capital institutions. The results show the following: (1) regarding the impact of EPU on the investment behavior of venture capital institutions, in China, EPU has a good news effect on the investment quantity of VC institutions. Under the influence of the macroeconomic performance level, the growth option effect, and the risk-seeking characteristics caused by information asymmetry lead VC institutions to regard EPU as an opportunity, thereby increasing investment. At the same time, EPU has a stimulating effect on the concentration degree of VC institutions in investment phases, investment industries, and investment regions. In other words, VC institutions can increase their investment in areas already covered to face the challenges brought by EPU and avoid risks. (2) Regarding the change of the impact of EPU on the investment behavior of venture capital institutions, the impact of EPU on the investment behavior of VC institutions changes with the investment state of institutions. The effect of EPU on promoting the investment quantity of VC institutions is enhanced as the investment quantity increases. The stimulating effect of EPU on the concentration degree of VC institutions in investment phases, investment industries, and investment regions is enhanced as the concentration degree increases. This shows that institutions with an excellent investment state are less affected by EPU.

Based on the research results above, this study proposes three policy recommendations for functional departments to better guide VC investment: (1) enhance market confidence and improve the macroeconomic performance level. In the case of a relatively high level of macroeconomic performance, positive factors such as call options have a strong capacity to affect the investment decisions of VC institutions in China. Therefore, we can amplify the promotion effect of EPU on investment and maximize the use of the opportunity feature of EPU by improving the macroeconomic performance level and enhancing the confidence of VC institutions. (2) Increase the transparency and continuity of economic policies. The increase in EPU can prompt VC institutions to increase the investment concentration degree,

thereby affecting the expansion and development of the innovation and entrepreneurship industry in China. This is not conducive to the subsequent optimization of China's microstructure in a period of economic transformation. Therefore, the transparency of economic policies is of great significance for both the market and enterprises. For the VC institutions in China, the enhancement of economic policy transparency is equivalent to reducing the high-impact market challenges and institutional challenges. Therefore, it can guide these institutions to form a more accurate development expectation, make diversified strategic adjustments to adapt to the plan, and accumulate momentum for the sustainable development of the market institutions in China. (3) Strengthen the guidance to key VC institutions. VC institutions that are characterized by large investment quantity and a low degree of concentration in investment phases, investment industries, and investment regions are greatly promoted and less discouraged by EPU. Therefore, the government can strengthen the guidance on the investment industry for key VC institutions to support key technological fields and use the relative concentration of strength to counter the unease that EPU brings to the entire market.

In addition, this study also has certain limitations. Improving the accuracy of the measurement index can increase the accuracy and persuasiveness of the results. Therefore, further research generated by this study should focus on finding a more comprehensive and accurate measurement index to describe EPU and provide more precise guidance for relevant departments.

Data Availability

The data used in this study were obtained from the Zero2IPO Database.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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References

[1] P. Gompers and J. Lerner, "The venture capital revolution," *The Journal of Economic Perspectives*, vol. 15, no. 2, pp. 145–168, 2001.

[2] T. Hellmann and M. Puri, "Venture capital and the professionalization of start-up firms: empirical evidence," *The Journal of Finance*, vol. 57, no. 1, pp. 169–197, 2002.

[3] H. Knight Frank, *Risk, Uncertainty and Profit*, Dover Publications, New york, USA, 1921.

[4] A. Schertler, *Dynamic Efficiency and Path Dependencies in Venture Capital Markets*, Springer Science & Business Media, Berlin, Germany, 2003.

[5] J. D. Luo and M. Y. Cheng, "Guanxi circles' effect on organizational trust: bringing power and vertical social exchanges into intraorganizational network analysis[J]," *American Behavioral Scientist*, vol. 59, no. 8, pp. 1024–1037, 2015.

[6] R. E. Lucas Jr. and E. C. Prescott, "Investment under uncertainty," *Econometrica*, vol. 39, no. 5, pp. 659–681, 1971.

[7] Y. Huang and P. Luk, "Measuring economic policy uncertainty in China," *China Economic Review*, vol. 59, Article ID 101367, 2020.

[8] H. Gulen and M. Ion, "Policy uncertainty and corporate investment," *Review of Financial Studies*, vol. 29, no. 3, pp. 523–564, 2016.

[9] U. Bhattacharya, P. H. Hsu, X. Tian, and Y. Xu, "What affects innovation more: policy or policy uncertainty," *Journal of Financial and Quantitative Analysis*, vol. 52, no. 5, pp. 1869–1901, 2017.

[10] J. A. Erkoyuncu, R. Roy, E. Shehab, and K Cheruvu, "Understanding service uncertainties in industrial product–service system cost estimation," *International Journal of Advanced Manufacturing Technology*, vol. 52, no. 9-12, pp. 1223–1238, 2011.

[11] A. K. Gupta and H. J. Sapienza, "Determinants of venture capital firms' preferences regarding the industry diversity and geographic scope of their investments," *Journal of Business Venturing*, vol. 7, no. 5, pp. 347–362, 1992.

[12] S. Dahiya and K. Ray, "Staged investments in entrepreneurial financing," *Journal of Corporate Finance*, vol. 18, no. 5, pp. 1193–1216, 2012.

[13] S. R. Baker, N. Bloom, and S. J. Davis, "Measuring economic policy uncertainty∗," *Quarterly Journal of Economics*, vol. 131, no. 4, pp. 1593–1636, 2016.

[14] P. Luk, M. Cheng, P. Ng, and K. Wong, "Economic policy uncertainty spillovers in small open economies: the case of Hong Kong," *Pacific Economic Review*, vol. 25, no. 1, pp. 21–46, 2020.

[15] E. Demir and O. Ersan, "Economic policy uncertainty and cash holdings: evidence from BRIC countries," *Emerging Markets Review*, vol. 33, pp. 189–200, 2017.

[16] X. Guangwei, S. Zheng, and L. Xing, "The influences of economic policy uncertainty on the preference of enterprise investment structure: evidence from China EPU index[J]," *Management Review*, vol. 32, no. 1, p. 246, 2020.

[17] W. Mbanyele, "Economic policy uncertainty and stock liquidity: the role of board networks in an emerging market," *International Journal of Emerging Markets*, 2021.

[18] S. Akron, E. Demir, J. M. Díez-Esteban, and C. D. Garcia-Gomez, "Economic policy uncertainty and corporate investment: evidence from the U.S. hospitality industry," *Tourism Management*, vol. 77, Article ID 104019, 2020.

[19] D. Li, N. E. Magud, and F. Valencia, "Corporate investment in emerging markets: financing vs. Real options channel," *IMF Working Papers*, vol. 15, no. 285, p. 1, 2015.

[20] J. Chen, F. Jiang, and G. Tong, "Economic policy uncertainty in China and stock market expected returns," *Accounting and Finance*, vol. 57, no. 5, pp. 1265–1286, 2017.

[21] B. S. Bernanke, "Irreversibility, uncertainty, and cyclical investment," *Quarterly Journal of Economics*, vol. 98, no. 1, pp. 85–106, 1983.

[22] R. McDonald and D. Siegel, "The value of waiting to invest," *Quarterly Journal of Economics*, vol. 101, no. 4, pp. 707–727, 1986.

[23] N. Bloom, S. Bond, and J. Van Reenen, "Uncertainty and investment dynamics," *The Review of Economic Studies*, vol. 74, no. 2, pp. 391–415, 2007.

[24] S. R. Jory, H. D. Khieu, T. N. Ngo, and H. V. Phan, "The influence of economic policy uncertainty on corporate trade

credit and firm value," *Journal of Corporate Finance*, vol. 64, Article ID 101671, 2020.
[25] D. Rodrik, "Political economy and development policy," *European Economic Review*, vol. 36, no. 2–3, pp. 329–336, 1992.
[26] R. S. Pindyck, "Irreversible investment, capacity choice, and the value of the firm," *The American Economic Review*, vol. 78, 1986.
[27] A. K. Dixit and R. S. Pindyck, *Real Options and Investment under Uncertainty-Classical Readings and Recent Contributions*p. 6, MIT Press, Cambridge, 1995.
[28] S. C. Myers, "Determinants of corporate borrowing," *Journal of Financial Economics*, vol. 5, no. 2, pp. 147–175, 1977.
[29] N. Bloom, "Fluctuations in uncertainty," *The Journal of Economic Perspectives*, vol. 28, no. 2, pp. 153–176, 2014.
[30] G. Segal, I. Shaliastovich, and A. Yaron, *Good and Bad Uncertainty: Macroeconomic and Financial Market Implications*, pp. 369–397, Elsevier, Amsterdam, Netherlands, 2015.
[31] N. Kulatilaka and E. C. Perotti, "Strategic growth options," *Management Science*, vol. 44, no. 8, pp. 1021–1031, 1998.
[32] S. Gilchrist, J. Sim, and E. Zakrajsek, "Divisions of research & statistics and monetary affairs uncertainty, financial frictions, and investment dynamics," *SSRN Electronic Journal*, 2014.
[33] M. C. Jensen and W. H. Meckling, "Theory of the firm: m," *Journal of Financial Economics*, vol. 3, no. 4, pp. 305–360, 1976.
[34] B. N. Ashraf and Y. Shen, "Economic policy uncertainty and banks' loan pricing," *Journal of Financial Stability*, vol. 44, Article ID 100695, 2019.
[35] C. D. Carroll and A. A. Samwick, "How important is precautionary saving?" *The Review of Economics and Statistics*, vol. 80, no. 3, pp. 410–419, 1998.
[36] X. Li, "Economic policy uncertainty and corporate cash policy: international evidence," *Journal of Accounting and Public Policy*, vol. 38, no. 6, Article ID 106694, 2019.
[37] L. Makosa, S. Jie, W. G. Bonga, M. Jachi, and L. Sitsha, "Does economic policy uncertainty aggravate financial constraints?" *South African Journal of Antarctic Research*, vol. 35, no. 2, pp. 151–166, 2021.
[38] L. Grilli, B. Mrkajic, and G. Latifi, "Venture capital in Europe: social capital, formal institutions and mediation effects," *Small Business Economics*, vol. 51, no. 2, pp. 393–410, 2018.
[39] H. J. Sapienza and M. A. Korsgaard, "Procedural Justice in eir," *Academy of Management Journal*, vol. 39, no. 3, pp. 544–574, 1996.
[40] W. Oi, "The desirability of price instability under perfect competition," *Econometrica*, vol. 29, no. 1, pp. 58–64, 1961.
[41] R. Hartman, "The effects of price and cost uncertainty on investment," *Journal of Economic Theory*, vol. 5, no. 2, pp. 258–266, 1972.
[42] A. B. Abel, "Optimal investment under uncertainty," *The American Economic Review*, vol. 73, no. 1, pp. 228–233, 1983.
[43] D. F. Caixe, "Corporate governance and investment sensitivity to policy uncertainty in Brazil," *Emerging Markets Review*, Article ID 100883, 2021.
[44] A. L. J. Ter Wal, O. Alexy, J. Block, and P. G. Sandner, "The best of both worlds: the benefits of open-specialized and closed-diverse syndication networks for new ventures' success," *Administrative Science Quarterly*, vol. 61, no. 3, pp. 393–432, 2016.
[45] D. De Clercq, P. K. Goulet, M. Kumpulainen, and M Makela, "Portfolio investment strategies in the Finnish venture capital industry: a longitudinal study," *Venture Capital*, vol. 3, no. 1, pp. 41–62, 2001.
[46] R. Martin, "The growth and geographical anatomy of venture capitalism in the United Kingdom," *Regional Studies*, vol. 23, 2006.
[47] B. S. Black and R. J. Gilson, "Venture capital and the structure of capital markets: banks versus stock markets," *Journal of Financial Economics*, vol. 47, no. 3, pp. 243–277, 1998.
[48] S. Manigart, A. Lockett, M. Meuleman et al., "Venture capitalists' decision to syndicate," *Entrepreneurship: Theory and Practice*, vol. 30, no. 2, pp. 131–153, 2006.
[49] J. Liao and H. Welsch, "Roles of social capital in venture creation: key dimensions and research implications∗," *Journal of Small Business Management*, vol. 43, no. 4, pp. 345–362, 2005.
[50] P. S. Adler and S. W. Kwon, "Social capital: prospects for a new concept," *Academy of Management Review*, vol. 27, no. 1, pp. 17–40, 2002.
[51] J. Florin, M. Lubatkin, and W. Schulze, "A social capital model of high-growth ventures," *Academy of Management Journal*, vol. 46, no. 3, pp. 374–384, 2003.
[52] D. Dang, H. Fang, and M. He, "Economic policy uncertainty, tax quotas and corporate tax burden: evidence from China," *China Economic Review*, vol. 56, Article ID 101303, 2019.
[53] S. N. Kaplan and A. Schoar, "Private equity performance: returns, persistence, and capital flows," *The Journal of Finance*, vol. 60, no. 4, pp. 1791–1823, 2005.
[54] E. Lutz, M. Bender, A. K. Achleitner, and C Kaserer, "Importance of spatial proximity between venture capital investors and investees in Germany," *Journal of Business Research*, vol. 66, no. 11, pp. 2346–2354, 2013.
[55] D. Acemoglu, S. Johnson, and J. A. Robinson, "The colonial origins of comparative development: an empirical investigation," *The American Economic Review*, vol. 91, no. 5, pp. 1369–1401, 2001.
[56] E. Miguel, S. Satyanath, and E. Sergenti, "Economic shocks and civil conflict: an instrumental variables approach," *Journal of Political Economy*, vol. 112, no. 4, pp. 725–753, 2004.
[57] R. Koenker and G. Jr. Bassett, "Regression quantiles," *Econometrica: Journal of the Econometric Society*, pp. 33–50, 1978.

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Research Article

The Effect of Green Intellectual Capital on Green Performance in the Spanish Wine Industry: A Structural Equation Modeling Approach

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Global environmental problems, such as global warming, pollution, or deforestation, are critical issues that require a rapid and common response. In this context, companies play a decisive role in achieving environmental objectives through the ecological knowledge they can store and manage. In this context, the present research focuses its interest on analyzing how the set of green intangibles possessed by organizations, i.e., Green Intellectual Capital (GIC), affects their Green Performance (GP). Specifically, the study shows how GP is influenced by GIC through the mediating role of the Green Innovation (GI) variable. Therefore, the research questions to be answered by this study are as follows: Does GIC influence environmental performance? Does GI mediate the GIC-GP relationship? What actions can companies take to improve their GP? There are several reasons that have led us to carry out this research. First, there is little empirical evidence of the relationships proposed in this study. Second, to the best of our knowledge, there is no previous research that has contextualized the relationships raised in the wine industry, thus representing an advance in the comprehension of the constructs studied. Third, GIC represents an incipient field of study that needs to be developed and established within the literature linked to Intellectual Capital (IC). In order to achieve the proposed objectives, data from a survey of 202 wineries in Spain were used and a quantitative approach was followed using Structural Equation Modeling (PLS-SEM). The results of the research indicate that there is a positive and significant relationship between GIC and GP. In addition, GI partially mediates the relationship between these two variables, playing a key role in the environmental management of wineries. The theoretical and practical contributions of the study improve the understanding of the relationships raised, being a pioneering study due to its contextualization in the wine industry, as well as providing a series of guidelines for both environmental managers and winemakers to improve their GP.

1. Introduction

Global warming, pollution, and deforestation are the manifestations of the accelerated growth of the world economy experienced in the last century [1]. These global environmental problems are critical and, therefore, require rapid and common responses, which has led to an intense academic debate on the need to achieve environmental sustainability [2].

Traditionally, activities aimed at environmental protection have conflicted with those aimed at economic performance [3]. On the one hand, earlier research claimed that the sole mission of managers was to maximize shareholder wealth [4]. On the other hand, recent studies indicate that companies must assume social and environmental responsibilities beyond purely economic ones [5, 6]. However, despite the ongoing debate on whether companies should be green or not, the need to balance their economic needs with environmental ones has begun to be recognized. This can be reflected in the growing interest of scholars in the study of environmental topics, such as green human resource management [7], green supply chain [8], sustainable

manufacturing [9], circular economy [10], green creativity [11], and organizational sustainability [12].

In this context, Green Innovation (GI) represents a win-win solution to the economic performance-environmental management conflict [13, 14]. Concern for the environment has created great opportunities for companies to improve the environmental characteristics of their products and processes in order to gain competitive advantages [15]. In fact, numerous studies demonstrate the positive relationship between the development of GIs and the improvement of the economic, social, and environmental performance of companies [16]. This type of innovation requires the integration of internal and external resources through the development of organizational capabilities and intangible resources [17]. Therefore, companies wishing to properly manage their GIs should prepare themselves by acquiring the necessary environmental capabilities and resources.

There are two main reasons why there is a growing interest in environmental management in organizations: (1) stringent environmental regulations [18]; and (2) increased customer awareness [19]. These factors require an added effort on the part of organizations to reduce the environmental impact of their products and processes by promoting GI such as packaging or eco-design [20], as well as to communicate the environmental practices developed within the organization in an appropriate way [21].

Despite the widespread tendency of organizations to develop sustainable business practices, it is still unclear what are the drivers of GI that, in turn, drive Green Performance (GP) [22, 23]. From the Natural Resource-based View (NRBV), intangibles such as knowledge, skills, and capabilities of the firm constitute essential elements for its environmental management and, as a consequence, for obtaining a competitive advantage, since, under the NRBV logic, competitive advantage is achieved from the sustainable activities of the organization. Therefore, intangible assets related to environmental protection can be considered antecedents of GI and GP. To accumulate and use intangible assets, companies can adopt different approaches framed under the three dimensions of Intellectual Capital (IC): human, structural, and relational capital [24]. However, the IC that incorporates sustainable concepts, i.e., Green Intellectual Capital (GIC), has emerged as an important field of study at present [25], being the construct currently used by scholars to understand the cause-effect relationships between such set of green intangible assets and other green variables.

The GIC brings together the research fields of IC and corporate sustainability, being understood as "the total stock of all kinds of intangible assets, knowledge, capabilities, and relationships, etc., on environmental protection or green innovation at the individual level and at the organizational level within a company" [18]. Therefore, GIC presents clear differences with IC, given that, while the IC approach understands sustainability as one of several intangible assets, GIC considers sustainability as the core of intangible assets, as well as the main driver for knowledge generation and management.

In this context, the present study aims to investigate the relationship between GIC-GP, as well as the mediating role of GI in this relationship. Three main reasons justify the need to carry out this study. First, there is little research that has provided empirical evidence on the relationships discussed above. Second, no previous research has been identified that addresses the relationships to be raised in the industry under analysis, i.e., the wine industry. Third, GIC is an incipient field of study that needs to be developed and established in the field of environmental management of organizations. To this end, as Chen [18] points out, there is a need for research on how GIC drives other variables, such as GP and GI. The research is of use for both academics and wine industry professionals, since, on the one hand, the research contributes to the academic literature by addressing the study of environmental intangibles and their relationship with GP, contextualizing the study in a sector where such relationships had not been previously addressed, and, on the other hand, the research is helpful for wine industry professionals by offering a series of recommendations for winemakers to improve their GIC and, as a consequence, their GP.

Thus, the present research aims to fill the existing gap in the literature through the study of GIC to advance the understanding of this construct, as well as its relationship with GP. In addition, GI is conceived as a mediating variable in this relationship. This study, therefore, aims to shed light on the ambiguity surrounding the GIC construct. It contributes to the existing debate in the environmental management literature, first, by analyzing the effect of GIC on GP in the wine industry and, second, by exploring the mediating role of the GI variable in clarifying this relationship. In particular, the research aims to answer the following two research questions: (1) Does GIC have a positive effect on GP? (2) Does GI mediate the GIC-GP relationship? (3) What actions can wineries take to improve their GP?

To answer the research questions, the article is structured as follows: First, after this introduction, Section 2 reviews the literature on the GIC effect on GP and GI, formulating, in turn, the hypotheses of the model proposed. Section 3 describes the methodology followed to achieve the research objectives, highlighting aspects related to data collection, measurements, and the statistical technique used. Section 4 examines the theoretical hypotheses put forward by discussing the results. Finally, Section 5 presents the most important theoretical and practical implications of the research, as well as the limitations and future lines of research.

2. Literature Review and Hypothesis Development

The widespread trend of organizations towards the development of more environmentally friendly business practices, as well as towards the generation of intangible assets and sustainable capabilities, such as GIC or GI, can be understood under the premises of the NRBV. The intellectual background of this approach has its origin in the seminal article written by Hart [26], who proposed this new vision under the logic of the Resource-based View (RBV), postulating that the strategy and competitive advantage of

organizations in the coming years would be based on capabilities that facilitate sustainable economic activity.

The NRBV represented a milestone in the environmental management literature by relating for the first time organizational intangibles, such as tacit knowledge or capabilities, to the environmental management of companies, offering, in addition, a new perspective focused on studying the interaction between the company and its natural environment, given that, under the principles of the theory formulated, the natural environment could act as an entry barrier for companies to generate sustainable competitive advantages [27]. Therefore, under this approach, environmental management is considered an essential element in business strategy.

As a consequence of the above, the role of intangible assets and capabilities has attracted the interest of several authors specialized in environmental management. Thus, while Russo and Fouts [28] stressed the importance of organizational routines and capabilities for developing organizational policies to prevent pollution, Aragón-Correa and Sharma [29] emphasized that the implementation of a successful environmental strategy depended, in large part, on the development of a series of organizational capabilities in which accumulated knowledge, the vision shared among the members of the organization and learning processes played a fundamental role. More recently, authors such as Yusoff et al. [30] and Yong et al. [31] have focused on analyzing the influence of existing green intangible assets in the organization on the development and sustainable performance of organizations.

IC is the theoretical construct in which organizational intangible assets aimed at economic, social, and environmental improvement best fit. This concept refers to the set of intangible resources (human, structural, and relational) that allow a company to obtain a sustainable competitive advantage over time [32], and its study has been developed under the Intellectual Capital-based View (ICBV) [33]. According to RBV, a firm's intangible resources are more likely to contribute to achieving and maintaining superior performance when they are combined or integrated [34]. However, the two main criticisms of such a view revolve around: (1) the lack of specificity and (2) the lack of a clear explanation for achieving competitive advantage [35, 36]. ICBV aims to overcome the limitations of RBV with regard to the measurement and evaluation of intangible assets by having a greater explanatory capacity to address the relationship between organizational intangibles and their performance/competitive advantage [37, 38].

Although IC has been widely studied under the ICBV, recently some authors have attempted to integrate such an approach into the environmental discourse through the GIC construct [25, 30, 31, 39–42]. ICBV enables organizations to implement stringent international regulations, comply with the growing environmental awareness of consumers, and create value for the organization [43]. For this reason, its role is fundamental to ensuring the success of the Sustainable Development Goals (SDGs) promoted by the United Nations [44].

Definitions of GIC are scarce in the environmental management literature. On the one hand, Chen [18], in his pioneering work, defined it as the total set of intangible assets, knowledge, and capabilities related to environmental protection or green innovation at the individual and organizational levels within an organization. Chen [45], on the other hand, defined it as the integration of green and environmental knowledge sources into the organization to enhance its competitive advantage. Similarly, Liu [46] conceived it as the sum of all organizational knowledge that enables the organization to improve environmental management to gain a competitive advantage. López-Gamero et al. [47], on the other hand, conceptualized it as "the total stock of all kinds of intangible assets, knowledge, capabilities, relationships, etc., on environmental protection at the individual and organizational levels of the firm". Along the same lines, Huang and Kung [43] stated that "green intellectual capital represents a company's intangible assets, including knowledge wisdom, capabilities, experience, and innovation in the field of environmental protection".

It should also be noted that, as suggested by Hart [26], the GIC consists of three dimensions: Green Human Capital (GHC), Green Structural Capital (GSC), and Green Relational Capital (GRC). On the one hand, GHC is defined as the set of knowledge, skills, abilities, capabilities, experiences, and commitments of employees about environmental protection that is embedded in employees and not in organizations [18], allowing an organization to recognize its intangible assets related to the environment and helping to implement green strategies in a given competitive environment. On the other hand, GSC is conceived as the set of organizational assets that show concern for environmental protection within the company [48]. Thus, Jardon and Dasilva [49] suggest that the organization's concern for environmental aspects is not modified only by human capital, since the support of organizational culture and systems is required to increase the level of environmental awareness in the organization. Finally, GRC refers to the set of intangible assets based on the existing relationships between the organization and suppliers, customers, network members, and partners to improve the environmental management of the company and thus achieve a competitive advantage. Therefore, GRC plays a key role in building strong and lasting relationships between the organization and its customers and suppliers.

In addition, GIC provides a better understanding of the background of GI. The ability to innovate is becoming increasingly important for companies in a dynamic global environment, with more and more companies willing to devote their resources to the development of GI [50]. The development of GI is a win-win solution for all stakeholders, overcoming the conflict between economic development and environmental protection. The "green" label is an incentive for continuous innovation, as it creates new market opportunities for companies to meet new consumer demands and, as a consequence, improve their performance. GI encompasses innovation in energy-saving technologies, pollution prevention, waste recycling, eco-friendly product design, and environmental management of companies [51].

There are two types of GI: green product innovation and green process innovation. On the one hand, green product innovation aims to modify product designs by using nontoxic compounds or biodegradable materials during the production process to reduce the impact of disposal on the environment and improve energy efficiency [52]. This includes improvements in the durability or recyclability of products, reduction of raw materials, selection of more environmentally appropriate raw materials, and elimination of hazardous substances [53]. For its part, green process innovation aims to reduce energy consumption during the production process or during the process that converts waste into a valuable item [54]. In particular, green process innovation includes reducing air emissions, reducing water consumption, improving resource and energy efficiency, and switching from fossil fuels to bioenergy [53]. Thus, companies that pioneer green innovation strategies can achieve and maintain various competitive advantages [55], gaining not only cost efficiency, but also economic profitability [16].

Therefore, both GIC and GI can lead to improved GP, understood as the positive consequences of green initiatives on the natural environment inside and outside the company [18]. The present research attempts to link both the NRBV and the ICBV to understand the relationships posed in the study between the variables GIC, GI, and GP. The following sections set out the hypotheses put forward in the research.

2.1. Green Intellectual Capital and Green Performance. Companies cannot ignore the increasing environmental concerns of customers and the pressures of international environmental regulations [25]. In this context, companies must consider the negative externalities generated by their activities on the environment through GIC management, which can not only reduce production waste and increase productivity but also increase the GP of the organization. This can be understood as the degree to which the activities carried out by the organization are environmentally friendly [56, 57].

GHC refers to the set of intangibles that are strongly rooted in employees' skills, being owned by the members of the organization and not by the employees. Therefore, this set of intangible assets represents a solid basis for obtaining a competitive advantage, given the difficulty for competitors to imitate these resources [58]. Thus, the GHC not only allows obtaining a sustainable competitive advantage, but also improves the GP of the organization, given that by acquiring greater environmental skills, the GHC will be higher and, as a consequence, the GP will also increase [59].

Thus, if the green knowledge stock of the workers, i.e., the GHC, is higher, the GP of the organization will also be higher [60]. The GHC represents a key piece, therefore, for the success of the GP of organizations, since the knowledge and skills of employees are essential to address the environmental challenges faced by the organization [61]. If a company develops a strong GHC, employees will have the necessary green knowledge to address environmental challenges. In fact, in the environmental management literature, a qualified GHC is considered to increase the organization's chances of gaining a sustainable advantage over time, since a more environmentally aware workforce will have better skills to address such organizational challenges and, therefore, contribute to a greater extent to the generation of sustained performance over time [62, 63].

Furthermore, the interaction between companies can significantly increase their ability to address their environmental challenges [64], as close and intense linkages between companies can be an effective means for them to collaborate in reducing the negative externalities generated by their activities. Frequent interaction between external partners can encourage the organization to exchange resources and capabilities, as well as establish stronger relationships [65], and can generate positive externalities that improve GP [61]. Therefore, the GRC can improve the GP by matching the environmental interests of the main stakeholders with those of the organization [66]. In addition, trust between companies and their stakeholders plays a fundamental role in the acquisition of green knowledge, which is subsequently translated into improved GP [67]. Likewise, it should be noted that although organizations may have environmental objectives among their priorities [68], they need to crystallize their environmental management through their corporate objectives, culture, strategies, and organizational structure [69]. The GSC is thus understood as an internal resource that can improve the achievement of environmental objectives [70, 71], by representing a set of green intangibles owned by the organization that allows it to improve its GP.

The GIC can improve GP in different ways. First, it allows for minimizing environmental costs. Second, it promotes green knowledge and awareness among employees. Third, it enables the company's adherence to the demanding standards and expectations present in governmental environmental regulations. According to Chuang and Huang [72], GP is rooted in the organization's ability to accumulate knowledge and resources related to environmental protection. Therefore, based on the above arguments, we put forward the following hypothesis:

H1. GIC has a positive effect on GP.

2.2. Green Intellectual Capital and Green Innovation. Numerous studies claim that a company's IC positively influences its capacity for innovation [73–76]. Similarly, companies that properly manage their GIC have several intangibles that favor GI, enabling the company to adapt to new challenges related to sustainable development [76, 77].

Human capital is an essential resource for developing organizational innovations since the knowledge possessed by employees represents the key intangible resource for developing innovations to compete in the current turbulent environment [78, 79]. Therefore, GI will be higher as the green knowledge stock of employees is higher [60]. GHC thus acts as a catalyst for GI, enabling organizations to stimulate their green product and process innovations [30]. This set of environmental intangibles provides a competitive advantage to the firm through improved eco-innovation capability [51]. GHC improves environmental practices at

the firm level [25], so firms with higher GHC tend to adopt more environmental innovations. Such a set of environmental intangibles have become a necessity to achieve environmental success for organizations [80], as companies wishing to develop GI need employees with high environmental knowledge. Also, GHC can generate an organizational climate in which risk, failure, and uncertainty are tolerated, thus facilitating the generation of creative ideas to develop GI. Therefore, if companies want to generate new green products and processes, they will need to develop their GHC.

Close relationships between employees and institutions facilitate innovation processes due to the faster flow of knowledge and its better utilization [81, 82]. In fact, numerous researchers claim that the relational capital of organizations, which is deployed through the exchange of ideas and knowledge between them, has a positive effect on organizational innovations [83–85]. From an environmental point of view, the tacit knowledge of employees [86], their social relationships [71], as well as inter-organizational relationships [8], serve to develop new technologies, ideas, products, and/or processes focused on preventing pollution caused by organizations, which can materialize in environmental product and process innovations. Therefore, the formation of a collaborative network between organizations to achieve environmental objectives, crystallized through the GRC, can foster the development of GI [87]. Therefore, as Huang and Kung [43] point out, GRC improves a company's cooperation and engagement with its customers, suppliers, and other stakeholders on environmental sustainability issues, which can translate into improved GI.

Despite developing GHC and GRC, if an organization does not have management systems and an adequate environmental culture, GI will be impossible to achieve. The elements of GSC, such as organizational structure, organizational culture, databases, and internal capabilities, directly increase the efficiency of GI, leading to higher firm profitability [88]. Moreover, organizational structure, culture, and policies lead to the improvement of innovation [89], so the integration of environmental knowledge in the organization can favor the development of GI. Thus, a company with a strong environmental culture fosters the acquisition of new green knowledge by employees, which is subsequently translated into GI [90]. Similarly, when such knowledge for the protection of the environment is codified, it can become systematically disseminated within the organization, to subsequently be used to develop GI [91]. Based on the above arguments, we propose the following hypothesis.

H2. GIC has a positive effect on GI.

2.3. Green Innovation and Green Performance. GI can not only increase the financial and social performance of companies but can also reduce the negative environmental impact generated by their activity [92], given that it is associated with the environmental management objectives of the organization [51, 93, 94]. Thus, GI is an essential capability for the successful environmental management of organizations, since it enables them to develop environmentally friendly products and processes.

NRBV advocates that pollution prevention, product stewardship, and sustainable development are key environmental strategies to improve GP and, as a consequence, gain competitive advantages [26, 27]. Therefore, organizations that are pioneers in the development of GI can achieve sustainable competitive advantages over time, since this type of innovation promotes the responsible and efficient use of raw materials in the production process, resulting in lower organizational costs [95], as well as improving product differentiation, which translates into higher consumer demand [96]. In this sense, it should be noted that GI allows for improving the ecological image of companies and, as a consequence, their GP [97], since they can incorporate ecological concepts in the design and packaging of their products [51]. In fact, the academic literature summarizes these two advantages under two dimensions: competitive advantage and GP. On the one hand, several studies affirm that GI, both in product and process, favors the achievement of competitive advantages [5, 70, 76]. On the other hand, scholars of the subject claim the existence of a positive relationship between GI and GP [91, 98, 99].

The implementation by organizations of GIs benefits organizations by enabling increased cost savings, improved environmental efficiency, and improved productivity, which directly contributes to competitive advantage [100]. In addition, the adoption of GIs potentially reduces pollution, hazardous toxic waste, and the cost of hazardous waste, while competently addressing external environmental pressures from other stakeholders with respect to environmental regulations [13, 100].

GP represents a major concern among managers since its improvement can imply compliance with strict environmental regulations and improve public perception of the products and services offered by the organization [101]. GI thus makes it possible to respond to the environmental needs of different stakeholders and to improve waste optimization. This is why companies that invest large resources to develop GI can: (1) reduce waste from their production, (2) increase their productivity, (3) comply with current regulations around environmental protection, (4) avoid sanctions from government agencies, (5) meet the environmental needs of stakeholders and (6) improve the differentiation of the organization. Therefore, in practice, the application of such type of innovation has the potential to improve the GP of organizations, with several researchers have demonstrated improved performance in terms of competitive advantage, green image, and GP [10, 12, 51, 102]. Thus, green products and process innovation are positively related to GP [100, 103, 104]. Based on the above arguments, we put forward the following hypothesis:

H3. GI has a positive effect on GP.

2.4. GI as a Mediating Variable in the GIC-GP Relationship. GHC refers to the set of knowledge, skills, and abilities possessed by employees in order to improve the

environmental management of the company [10], favoring a climate conducive to tolerating failure and risk involved in the development of GI [12]. Thus, companies use the green knowledge of employees to develop GI to improve their GP [8]. Likewise, companies operating under strict environmental legislation understand the importance of GHC, given that this set of intangibles based on employees' skills, knowledge and creativity enables compliance with environmental regulations and encourages the adoption of strategies based on GI that, in turn, derive higher GP [55]. Thus, GHC allows a company to recognize its intangible green assets, facilitating the development and implementation of GIs to improve GP [61].

GRC, on the other hand, fosters GI development by reducing transaction and information search costs. Thus, when companies promote GRC in their environmental operations, they can better develop GI to minimize environmental impact and attract environmentally conscious customers. GRC is therefore a key resource for achieving the company's environmental goals from its relationships with suppliers, customers, and institutions [105]. Organizations should strive to integrate the green knowledge generated from the GRC, as GI is partly derived from this knowledge [106]. Therefore, GRC can increasingly increase GP through GI.

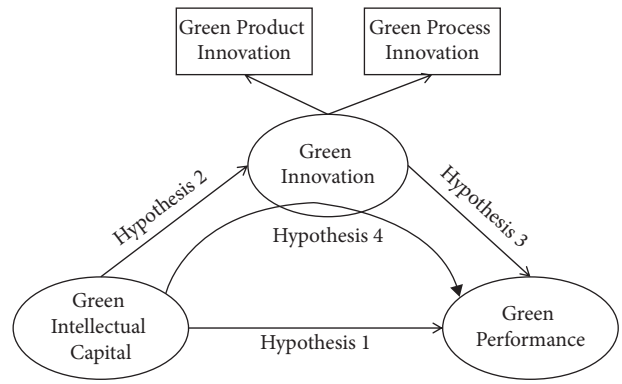
The GSC encompasses the existing codified environmental knowledge within an organization. This stock of organizational knowledge can favor GI, since the production of new products and the development of new processes often involve the application of this knowledge [107], positively influencing the GP of the organization [108]. Organizational structures and policies can positively influence innovations aimed at preserving the environment, and such innovations, in turn, can positively influence the GP of firms [109]. The codification of the environmental knowledge generated in the organization influences the GP of the organization, increasing the chances of successfully developing GIs [61]. Therefore, GSC, understood as the codified green knowledge possessed by the firm positively influences the GP of organizations by facilitating GI. Recently, Wang and Juo [61] demonstrated the mediating effect of GI on the GIC-GP relationship. However, there is little academic literature that has addressed such a mediating effect and, therefore, there is no certainty of such a relationship. Therefore, one of the main objectives of this study is to examine whether GI acts as a mediating variable in the GIC-GP relationship. Based on the above arguments, we propose the following hypothesis:

H4. GI mediates the relationship between GIC and GP.

Figure 1 shows the theoretical model proposed with the hypotheses to be tested.

3. Methodology

The methodological section of this research is divided into three blocks: (1) sample and population, (2) research questionnaire, and (3) analysis technique. Each of these blocks is described in detail below.



Source: own elaboration

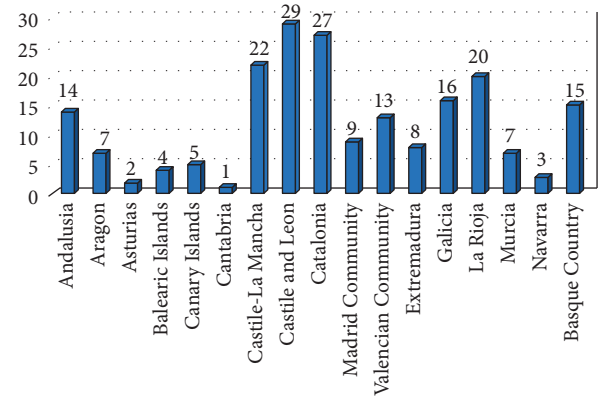
Figure 1: Proposed theoretical model. Source: own elaboration.

3.1. Sample and Population. Our research is contextualized in the Spanish wine industry for three main reasons. First, the Spanish wine industry has been selected as the unit of analysis given its importance for the economic and social development of Spain. Thus, according to the latest data provided by the International Organization of Vine and Wine (OIV), Spain stands out for its preferential position in the global wine industry, being the country with the largest vineyard surface area in the world and the largest exporter in volume. Second, in recent years various studies have emphasized the importance of knowledge as a key strategic factor in the modern wine industry [110–112]. Thus, while in the classic industrial approach, the wine sector was oriented to obtaining high yields per hectare as a formula for generating higher income, today, wineries are characterized by the intensive use of knowledge to reduce yields, prevent pests, enhance the expression of local varieties or take care of winemaking and aging in detail. Therefore, we consider it necessary to analyze green intangibles and their relationship with other constructs, being an increasingly knowledge-intensive industry. Third, no previous research has analyzed the relationships of the theoretical model proposed in the wine industry, which represents an opportunity to advance knowledge and understanding of the constructs under study.

The study population, therefore, is made up of companies in the Spanish wine industry, specifically those included in the National Code of Economic Activities (CNAE, for its Spanish acronym) 1102. According to the Sistema de Análisis de Balances Ibéricos (SABI) database, this CNAE code has a total of 4,373 companies, more than 99% of which are micro-enterprises and SMEs. A structured questionnaire based on the literature review was used for data collection in order to achieve greater representativeness in the results. First, the content of the questionnaire was validated through a pretest in which environmental managers of wineries and winemakers participated to validate the clarity and validity of the items used. Subsequently, the survey was distributed online using the Qualtrics application during the last 4 months of 2021. After the data collection process, a total of 216 observations were initially obtained. However, after the data cleaning process, 202 questionnaires were considered valid, this being the final sample (94.3% of the total number of responses). This sample size is valid for obtaining robust

data through structural equation modeling, since a minimum sample size of 100 is required for the relationships between variables to be analyzed [113]. Likewise, it can be seen that the Spanish autonomous communities most represented in our sample are Castile and Leon (14.36%), Catalonia (13.37%), Castile La-Mancha (10.89%), and La Rioja (9.90%), all communities being represented to a greater or lesser extent in our sample (see Figure 2). This order is in line with the population under study, given that, according to the data provided by the SABI database, the communities with the most wineries are Castilla and León (17.35%), Catalonia (15.64%), and Castilla La-Mancha (11.31%). Furthermore, with regard to the size of the companies, 99.56% of the wineries in our sample are Small and Medium-sized Enterprises (SMEs), coinciding with the size of the companies belonging to the population studied, given that, based on the data on workers provided by the SABI database, 98.76% of Spanish wineries are SMEs.

3.2. Research Questionnaire. To ensure consistency, reliability, and validity in the measurement of the variables, scales previously validated online in previous research were used (see Table 1). For the measurement of GIC, we used the scale employed by Zaragoza-Sáez et al. [96], which was measured by the authors using a 7-point Likert-type scale with seven items, taking as a reference the measures provided in the studies conducted by Chen [18], Huang and Kung [43], and Chang and Chen [48]. For the measurement of GI, the scale used by Chen [45] was used, conceiving the construct as the development of environmentally friendly products and processes that modify the design of an existing product and/or process to reduce any negative impact on the environment. On the one hand, green product innovation refers to the introduction of environmentally friendly materials, environmentally friendly packaging, product recovery and recycling, and eco-labeling [51]. On the other hand, green process innovation relates to a company's ability to improve existing processes, as well as to develop new ones that generate savings and avoid pollution, save energy, favor waste recycling, or decrease toxicity in processes [51]. In that sense, we followed Chen's approach [45] by considering GI as a second-order construct formed by green product innovation (4 items) and green process innovation (4 items) as first-order constructs. As with the GIC, the measurement scale used for this variable was Likert-type with seven response options (1–7). To measure GP, the 7-point Likert-type scale with 5 items by Paillé et al. [114] was used, which is based, in turn, on the five-item scale developed by Chow and Chen [115]. Finally, the size was introduced as a control variable, reporting the size of each organization according to the number of employees through the commonly known categorical classification that groups the different companies into microenterprises if they have up to 10 workers, small companies when they have 10 to 50 workers, medium-sized companies if they employ between 50 and 250 workers, and large companies when they have more than 250 workers [116].



Source: own elaboration

Figure 2: Distribution of the companies in the sample by the autonomous community. Source: own elaboration.

3.3. Analysis Technique. The analysis technique used was partial least squares structural equation modeling (PLS-SEM), using the SmartPLS v. 3.3.3 software. This methodology makes it possible to analyze a network of theoretical relationships between variables, some of which may be latent, i.e., not observable. This makes PLS-SEM particularly useful for developing research in the field of social sciences since most of the concepts studied by the discipline are not directly observable [117]. In fact, the technique has experienced accelerated growth and acceptance in the field of social sciences during the last decade [118], particularly in the area of Management [119], the field in which our research is framed.

The choice of this technique for this study is based on several reasons. First, the minimum sample size for applying PLS-SEM is not very demanding [120], which is an advantage for the conduct of our study since the research sample ($n = 202$) is not very large. Thus, Reinartz et al. [121] consider that 100 observations should be the minimum sample size to give robustness to the results obtained in PLS-SEM. Second, our research establishes direct and indirect relationships between constructs, recommending the use of PLS-SEM in these cases as it can effectively handle these aspects [122]. Third, in our study, GI is a second-order construct, and this multidimensional variable can be effectively estimated in PLS [123]. Fourth, the PLS-SEM technique has been used previously to analyze the wine industry, so it is a valid research method for our investigation.

Likewise, it is important to note that there are several reasons to justify the use of the PLS-SEM technique as opposed to covariance-based structural equation modeling (CB-SEM). First, while CB-SEM is used when testing existing theory, PLS-SEM is appropriate in the exploratory phase for theory building and prediction [118]. Research addressing GIC, as well as its linkage to other constructs, is recent in the academic literature, so the field of study is still in the process of construction and consolidation. This justifies the preferential use of PLS-SEM over the CB-SEM approach in this study. Second, while for the use of the CB-SEM technique the properties of the normal distribution

Table 1: Measurement of the variables analyzed.

Construct	Items	Measure	Source
Green intellectual capital (GIC)	*GIC 1.* Our employees care about the environment *GIC 2.* Our employees have the knowledge and skills to protect the environment *GIC 3.* Our employees cooperate in working groups to address environmental issues *GIC 4.* Our employees cooperate with our suppliers to protect the environment *GIC 5.* Our employees cooperate with our customers/distributors to protect the environment *GIC 6.* Our company implements innovations to protect the environment *GIC 7.* Our company invests in facilities to protect the environment	Likert scale (1 = strongly disagree; 7 = strongly agree)	Zaragoza-sáez et al. (2020)
Green product innovation (GPTI)	*GPTI 1.* The company chooses the product materials that produce the least amount of contamination to carry out product development or design *GPTI 2.* The company chooses the product materials that consume the least energy and resources to carry out product development or design *GPTI 3.* The company uses the least amount of materials to compose the product to carry out the development or design of the product *GPTI 4.* The company would deliberate with circumspection whether the product is easy to recycle, reuse and decompose to carry out product development or design	Likert scale (1 = strongly disagree; 7 = strongly agree)	Chen (2008)
Green process innovation (GPSI)	*GPSI 1.* The emission of hazardous substances or wastes is effectively reduced in the manufacturing process *GPSI 2.* In the manufacturing process, waste and emissions are recycled to enable their treatment and reuse *GPSI 3.* Water, electricity, coal, or oil consumption is reduced in the manufacturing process *GPSI 4.* In the manufacturing process, the use of raw materials is reduced		
Green performance (GP)	*GP 1.* Our company has reduced waste and emissions from operations compared to its competitors over the past 5 years *GP 2.* Our company has reduced the environmental impact of its products/services compared to its competitors over the last 5 years *GP 3.* Our company has reduced its environmental impact by establishing partnerships compared to its competitors over the past 5 years *GP 4.* Our company has reduced the risk of environmental accidents, spills, and emissions compared to its competitors over the last 5 years *GP 5.* Our company has reduced purchases of nonrenewable materials, chemicals, and components compared to its competitors over the past 5 years	Likert scale (1 = strongly disagree; 7 = strongly agree)	Paillé et al. (2014)

Source: own elaboration.

must be strictly complied with, for the PLS-SEM technique it is not necessary to assume a normal distribution of the data as it is a nonparametric method [119]. Therefore, as far as the properties of the data distribution are concerned, the PLS-SEM technique has greater flexibility compared to CB-SEM. Third, the PLS-SEM technique is preferable when there are second-order variables in the model to be tested [117]. Given the multidimensional nature of the GI variable, consisting of green process innovation and green product innovation, the PLS-SEM approach is more appropriate than CB-SEM. Fourth, the minimum sample size of the study could allow us to apply both the PLS-SEM and the CB-SEM approach, since while the minimum sample size to apply PLS-SEM is 100, to apply CB-SEM a minimum sample size of 200 is required [118]. In this regard, it has been decided to select the PLS-SEM approach since the sample size is clearly higher than the minimum required, which increases the precision of the model estimates. Fifth, several previous investigations addressing the relationships between GIC, GI, and GP constructs have

used PLS-SEM, which confirms the suitability of the technique to test the relationships proposed.

4. Results

Given the multidimensional nature of the GI variable, we applied the two-stage model based on "latent variable scores" [124] to obtain the results. First, the aggregate scores of the first-order constructs were calculated. Second, these aggregate scores were used as indicators of the second-order construct. Next, based on the recommendations of Hair et al. [118], we present the results of the model in three blocks: (1) the evaluation of the global model, (2) the evaluation of the measurement model, and (3) the evaluation of the structural model.

4.1. Evaluation of the Global Model. The proposed model presents a standardized root mean square residual (SRMSR) of 0.047 < 0.08 [124], which means that the model has a good global fit. In addition, it also meets the more stringent requirement of Carmines and Zeller [125], who considers that SRMS must be less than 0.05 for there to be an adequate global fit of the model.

Once the SRMR fit criterion was checked, it was verified whether this indicator together with the unweighted least squares discrepancy (d_ULS) and the geodesic discrepancy d_G was within the confidence range after bootstrapping. As can be seen in Table 2, all values are below HI95 and HI99. Therefore, the results imply that this model cannot be rejected [118].

Table 3 shows the mean, maximum and minimum values, as well as the standard deviation for each variable are analyzed. As can be seen, the minimum and maximum values of the constructs GIC, GI, and GP are 1 and 7 respectively. This is because these are the minimum and maximum values of the Likert scale used. Likewise, while the minimum size of the wineries is 1, referring to the number of workers, the maximum value of the size variable is 262, which is the maximum value of the number of workers that make up a winery among the companies in the sample. Similarly, there are 10 workers on average among the companies in the sample, with the average of the three remaining variables being around values close to 5. Of the four constructs analyzed, the GIC is the one with the greatest dispersion to the average (1.496), while the size is the one with the least dispersion (0.969).

4.2. Measurement Model. To analyze the quality of the measurement model, the following criteria set forth by Hair et al. [118] were followed: (1) and analyze the reliability of the individual indicators through their external loadings (λ), (2) assess the internal consistency reliability through Cronbach's alpha and composite reliability, (3) check the convergent validity through the average variance extracted (AVE) and (4) to analyze the discriminant validity the Heterotrait-Monotrait criterion (HTMT).

First, as indicated in Table 4, all the indicators of the variables analyzed do meet the requirement of individual item reliability, since their loadings exceed the value of 0.707 [126]. It is, therefore, possible to state that the different indicators present sufficient levels of reliability at the individual level. Second, it is possible to state that all the constructs meet the reliability criterion of internal consistency since both Cronbach's alpha and composite reliability (ρc) exceed the value of 0.8. Third, the constructs meet the requirement of convergent validity, since their AVE measures exceed the 0.5 level [127]. Therefore, each construct explains more than half of the variance of its indicators. Finally, Table 5 shows the discriminant validity test following the HTMT criterion. As can be seen, the values of the GIC, GI, and GP are clearly lower than 0.85 [128]. This means that each construct is unique and, therefore, captures phenomena not represented by other constructs in the model.

Table 2: Overall model fit.

	Value	HI95	HI99
SRMR	0.047	0.052	0.063
d_ULS	0.641	0.718	0.844
d_G	0.765	0.816	0.921

Source: compiled by authors.

Table 3: Values of the mean, minimum value, maximum value, and standard deviation of the variables analyzed.

	Mean	Min	Max	Standard deviation
GIC	4.944	1	7	1.496
GI	5.127	1	7	1.231
GP	4.873	1	7	1.343
Size	10.242	1	262	0.969

Source: compiled by authors.

4.3. Structural Model. Once it has been confirmed that the measures of the constructs are reliable and valid, the next step is to address the assessment of the structural model. This assessment involves examining the predictive ability of the model and the relationships between constructs. Following the indications followed by Gilinsky et al. [129], to evaluate the structural model we analyzed the path coefficients, the R-Squared level, and the predictive relevance of Q2.

First, before evaluating these indicators, we examined the presence of problems related to collinearity in the structural model. This is due to the need to avoid the presence of multicollinearity between the antecedent variables of each of the endogenous constructs. According to Hair et al. [118], there are indications of collinearity when the variance inflation factor is greater than 5 (VIF > 5). Therefore, values greater than five of the endogenous constructs imply critical levels of collinearity. In this sense, the VIF values obtained in this work do not exceed the maximum value in any of the cases (see Table 6). In addition, there is no unobserved heterogeneity in the sample data.

Through Figure 3 it can be observed how the results regarding R-Squared and β are based on a bootstrap test with 5000 subsamples. The direct and indirect effects of GIC on GP of wineries have been tested, finding both positive and

Table 4: Measurement model: external loadings, construct reliability, and convergent validity.

Construct/items	Outer loadings	Rho (Pa)	Cronbach's alpha	Ave
Green intellectual capital (GIC)		0.883	0.883	0.589
GIC 1. Our employees care about the environment	0.759			
GIC 2. Our employees have the knowledge and skills to protect the environment	0.781			
GIC 3. Our employees cooperate in working groups to address environmental issues	0.719			
GIC 4. Our employees cooperate with our suppliers to protect the environment	0.833			
GIC 5. Our employees cooperate with our customers/distributors to protect the environment.	0.86			
GIC 6. Our company implements innovations to protect the environment	0.71			
GIC 7. Our company invests in facilities to protect the environment	0.724			
Green innovation (GI)		0.948	0.945	0.725
GPTI 1. The company chooses the product materials that produce the least amount of contamination to carry out product development or design	0.882			
GPTI 2. The company chooses the product materials that consume the least energy and resources to carry out product development or design	0.903			
GPTI 3. The company uses the least amount of materials to compose the product to carry out the development or design of the product	0.881			
GPTI 4. The company would deliberate with circumspection whether the product is easy to recycle, reuse and decompose to carry out product development or design	0.885			
GPSI 1. The emission of hazardous substances or wastes is effectively reduced in the manufacturing process	0.89			
GPSI 2. In the manufacturing process, waste and emissions are recycled to enable their treatment and reuse	0.801			
GPSI 3. Water, electricity, coal, or oil consumption is reduced in the manufacturing process	0.838			
GPSI 4. In the manufacturing process, the use of raw materials is reduced	0.713			
Green performance (GP)		0.936	0.928	0.78
GP 1. Our company has reduced waste and emissions from operations compared to its competitors over the past 5 years	0.906			
GP 2. Our company has reduced the environmental impact of its products/services compared to its competitors over the last 5 years	0.937			
GP 3. Our company has reduced its environmental impact by establishing partnerships compared to its competitors over the past 5 years	0.786			
GP 4. Our company has reduced the risk of environmental accidents, spills, and emissions compared to its competitors over the last 5 years	0.87			
GP 5. Our company has reduced purchases of nonrenewable materials, chemicals, and components compared to its competitors over the past 5 years	0.907			

Source: compiled by authors.

Table 5: Measurement model: discriminant validity.

	GIC	GI	GP	Size
GIC				
GI	0.725			
GP	0.486	0.553		
Size	0.170	0.107	0.224	

Source: compiled by authors.

Table 6: Analysis of collinearity in the model through VIF values.

	GIC	GP	GI	Size
GIC		1.778	1.000	
GP				
GI		1.779		
Size		1.013		

Source: compiled by authors.

statistically significant effects (see Table 7). This implies that the GI partially mediates the relationship between the GIC and GP, given the direct (0.169) and indirect (0.261) effects are positive and significant, with a strong total effect of GIC on GP of 0.430 ($p \leq = 0.01$). Therefore, all four hypotheses are supported. Table 8 also shows the effect sizes (f^2), i.e., the degree to which an exogenous construct contributes to explaining a given endogenous construct in terms of R^2 [130]. In this case, the most representative f^2 values correspond to the GIC for the GI construct (0.775) and GI for the GP construct (0.108). Finally, to analyze the quality of the model, Geisser's test (Q^2) was performed, which must have estimated values above 0 ($Q^2 > 0$). As can be seen in Table 9, an average predictive relevance of the model was observed because the Q^2 values are above 0.25 [111]. Regarding the control variables, the results show that the size of the wineries has a positive and significant impact on the GP.

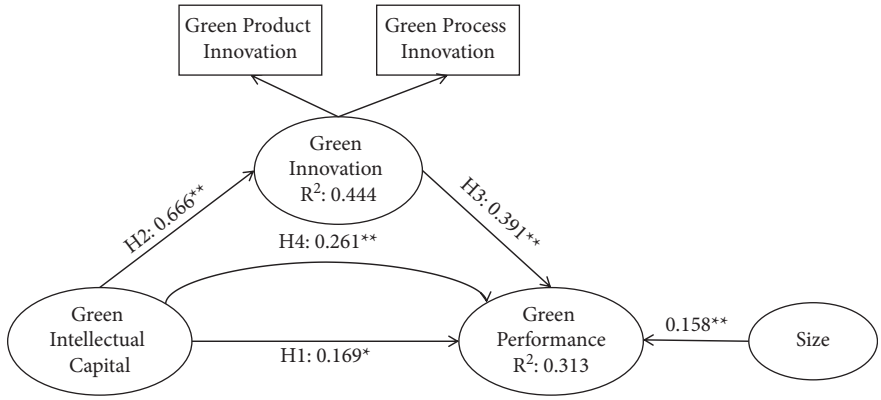


Figure 3: Theoretical model with R-squared, path coefficients (β), and significance. Source: own elaboration.

Table 7: Results of the structural model for the mediation model.

Direct effects	Path coefficient	t-value	p-value	95% BCCI	Hypothesis supported
GI - > GP	0.391	3.635	$\leq = 0.01^{**}$	[0.195; 0.551]	H3 supported
GIC - > GI	0.666	13.437	$\leq = 0.01^{**}$	[0.583; 0.748]	H2 supported
GIC - > GP	0.169	1.737	0.042^{*}	[0.069; 0.231]	H1 supported
Indirect effects	Path coefficient	t-value	p-value	95% BCCI	Hypothesis supported
GIC - > GI - > GP	0.261	3.572	$\leq = 0.01^{**}$	[0.134; 0.379]	H4 supported

Notes: BCCI: bias corrected confidence intervals; $^{*}p < 0.05$; $^{**}p < 0.001$. Source: compiled by authors.

Table 8: Effect sizes (f^2) of the analyzed variables.

	GP	GI
GIC	0.036	0.775
GI	0.108	
Size	0.048	

Source: compiled by authors.

Table 9: Construct cross validated redundancy.

	SSO	SSE	Q^2 (=1-SSE/SSO)
GI	1616	1103.561	0.317
GIC	1414	1414	
GP	1010	771.32	0.256
Size	202	202	

Source: compiled by authors.

Therefore, it could be interesting to analyze the differences in environmental management between large winery groups and small wineries.

The results of this research suggest that the development of GIC in wineries can lead to higher GP. Moreover, these intangibles not only generate greater ecological performance but also favor the formation of key organizational capabilities, such as GI, thus strengthening the GIC-GP relationship. The positive and significant relationship between GIC on GIP is in line with the results obtained by Yusliza et al. [66] and Wang and Juo [61], which demonstrate such a relationship for Malaysian and Taiwanese manufacturing industries, respectively. In addition, GIC acts as a catalytic variable for GI. In this regard, Chen & Chang [20] demonstrate a positive and significant relationship between GHC and GI performance. In contrast, Chang [131] states that GHC does not directly affect GI, but indirectly through green adaptive capacity. Chen et al. [51] assert through their research that GIC has an indirect impact on GI through GSC. Ali et al. [119] show that GHC and GSC increase significantly with GI adoption. Jirakraisiri et al. [40], on the other hand, show that all three GIC dimensions positively and significantly influence the adoption of GI. In the present study, we analyzed the GIC construct in a unified way to understand the relationship of environmental intangibles to CG holistically. On the other hand, the mediating effect of GI on the GIC-GP relationship has been sparsely explored in the academic literature. However, through the joint understanding of the NRBV and ICV approaches, the mediating role that the GI variable can play in such a relationship has been corroborated.

5. Conclusions and Implications

The results presented in the present research are relevant for the academic community, as well as for companies and professionals in the wine industry, as they improve the knowledge about the relationship between GIC and GP in the wine industry.

Wineries are facing increasing pressures to improve their environmental sustainability [132], as the environment, the community, and the local economy can be negatively affected by their activity. The wine industry is facing several exogenous factors that threaten its survival, such as rising energy prices, water scarcity, increasing environmental awareness among stakeholders, and climate change [133].

These factors, together with the knowledge of winemakers and wineries, can drive the adoption of sustainable practices that subsequently culminate in product and process innovations to improve the GP of wineries [129]. For this reason, the analysis proposed in the present research becomes particularly relevant, since the high impact of GIC on wineries' GP has been empirically demonstrated. Moreover, as demonstrated in the research, this positive effect is partially mediated by GI. Therefore, wineries that promote their GHC, GSC, and GRC will be able to improve their GP, as well as their capacity to develop innovations aimed at protecting the environment.

There are several theoretical and practical implications derived from our research. Regarding the theoretical contributions, the results of the present research contribute to the environmental management and IC literature, providing practical evidence in the Spanish wine industry. In particular, the research empirically demonstrates the positive and significant effect of GIC development on wineries' GP, as well as the mediating effect of GI on this relationship. These results are consistent with recent empirical research such as that of Wang and Juo [61] contextualized in Taiwan's high-tech sector. However, further analysis of the constructs and their relationships should be pursued, as the academic literature addressing these relationships is very sparse. Therefore, we encourage environmental management researchers to continue to delve deeper into these relationships in future publications. The practical implications, therefore, allow us to answer the first two research questions, given that (1) there is a positive and significant relationship between GIC on GP, and (2) GI partially mediates this relationship. It is important to note that, to the best of our knowledge, no previous research has contextualized the relationships raised in the wine industry, which represents an advance in the understanding of the constructs studied, as well as in the comprehension of the environmental management of wineries.

Regarding the practical contribution of the study, the results presented in this research can play a key role in the environmental management decisions of environmental managers and winery winemakers. In this regard, from the GHC point of view, winery employees can develop codes of good environmental practices, organize training and environmental awareness sessions, as well as attend seminars and workshops to improve their green knowledge. As for the GSC, wineries can develop circular economy programs, computer systems to measure carbon and water footprint, eco-efficient facilities, a brand linked to sustainability, certifications that endorse their environmental commitment, a flat organizational structure through which green knowledge flows, an organizational culture built on the pillars of sustainability, as well as constant investments in R&D&i. As far as the GRC is concerned, the link between wineries and their stakeholders should be fostered, since such relationships can improve their green knowledge of the companies and, consequently, their environmental management. These organizational practices make it possible to accumulate a series of green intangibles that have a positive impact on the wineries' GP. Likewise, GI such as the development of organic wines, the technological improvement of agricultural soils, the valorization of waste, as well as the control of damages and climatic risks, can enhance the GIC-GP relationship. The practical implications provide an answer to the third research question, given that through actions aimed at improving employees' green knowledge (GHC), codifying the organization's environmental knowledge (GSC) and fostering relationships between different stakeholders (GRC), companies can improve their GP. The research can therefore be useful to winemakers who are thinking of improving their GP and/or their GIs, given that the actions proposed to improve the GHC, GSC, and GRC can lead to the improvement of the GP through the GI.

Despite the important contributions made in the article, it is important to highlight the existence of certain limitations. First, the relevance of the topic makes it necessary to extend this analysis to other wine-producing countries. In this sense, the effect of the GIC on the performance of wineries at the international level would be of great interest, and comparisons could be made between New World and Old World wine-producing countries. Second, there is a limitation inherent to cross-sectional studies, since they do not allow us to examine relationships over an extended period of time. Specifically, it would be interesting to know the evolution and temporal trajectory of the study carried out. For this reason, it seems relevant to us as a future line of research to analyze the companies that participated in the survey through longitudinal analysis. This implies that these companies should be willing to participate in the coming years in order to be able to investigate their evolution in an increasingly competitive, technological, and international business context. In addition, we could further investigate the role that winery size can play in GIC and GP. In fact, as a future line of research, we propose to carry out a multigroup analysis in which the differences in the model proposed according to the size of the wineries (SMEs or large companies) can be seen.

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.

References

[1] Y. Jin, C. Cheng, and H. Zeng, "Is evil rewarded with evil? The market penalty effect of corporate environmentally irresponsible events," *Business Strategy and the Environment*, vol. 29, no. 3, pp. 846–871, 2020.

[2] L. Hsueh, "Opening up the firm: what explains participation and effort in voluntary carbon disclosure by global businesses? An analysis of internal firm factors and dynamics," *Business Strategy and the Environment*, vol. 28, no. 7, pp. 1302–1322, 2019.

[3] A. Scheidel, L. Temper, F. Demaria, and J. Martínez-Alier, "Ecological distribution conflicts as forces for sustainability:

an overview and conceptual framework," *Sustainability Science*, vol. 13, no. 3, pp. 585–598, 2018.

[4] M. Friedman, *Capitalism and Freedom*, University of Chicago Press, Chicago, 1962.

[5] C. H. Chang, "The influence of corporate environmental ethics on competitive advantage: the mediation role of green innovation," *Journal of Business Ethics*, vol. 104, no. 3, pp. 361–370, 2011.

[6] R. Stewart and M. Niero, "Circular economy in corporate sustainability strategies: a review of corporate sustainability reports in the fast-moving consumer goods sector," *Business Strategy and the Environment*, vol. 27, no. 7, pp. 1005–1022, 2018.

[7] A. A. Zaid, A. A. Jaaron, and A. Talib Bon, "The impact of green human resource management and green supply chain management practices on sustainable performance: an empirical study," *Journal of Cleaner Production*, vol. 204, pp. 965–979, 2018.

[8] S. Yildiz Çankaya and B. Sezen, "Effects of green supply chain management practices on sustainability performance," *Journal of Manufacturing Technology Management*, vol. 30, no. 1, pp. 98–121, 2019.

[9] S. H. Abdul-Rashid, N. Sakundarini, R. A. Raja Ghazilla, and R. Thurasamy, "The impact of sustainable manufacturing practices on sustainability performance," *International Journal of Operations & Production Management*, vol. 37, no. 2, pp. 182–204, 2017.

[10] U. Awan and R. Sroufe, "Sustainability in the circular economy: insights and dynamics of designing circular business models," *Applied Sciences*, vol. 12, no. 3, p. 1521, 2022.

[11] T. A. Bhutto, R. Farooq, S. Talwar, U. Awan, and A. Dhir, "Green inclusive leadership and green creativity in the tourism and hospitality sector: serial mediation of green psychological climate and work engagement," *Journal of Sustainable Tourism*, vol. 29, no. 10, pp. 1716–1737, 2021.

[12] U. Awan, A. Khattak, S. Rabbani, and A. Dhir, "Buyer-driven knowledge transfer activities to enhance organizational sustainability of suppliers," *Sustainability*, vol. 12, no. 7, p. 2993, 2020.

[13] M. Porter and C. van der Linde, "Green and competitive: ending the stalemate," *Harvard Business Review*, vol. 73, no. 5, pp. 120–134, 1995.

[14] S. K. Singh, M. D. Giudice, R. Chierici, and D. Graziano, "Green innovation and environmental performance: the role of green transformational leadership and green human resource management," *Technological Forecasting and Social Change*, vol. 150, Article ID 119762, 2020.

[15] H. Zameer, Y. Wang, and H. Yasmeen, "Reinforcing green competitive advantage through green production, creativity and green brand image: implications for cleaner production in China," *Journal of Cleaner Production*, vol. 247, Article ID 119119, 2020.

[16] S. Asadi, S. OmSalameh Pourhashemi, M. Nilashi et al., "Investigating influence of green innovation on sustainability performance: a case on Malaysian hotel industry," *Journal of Cleaner Production*, vol. 258, Article ID 120860, 2020.

[17] T. Lampikoski, M. Westerlund, R. Rajala, and K. Möller, "Green innovation games: value-creation strategies for corporate sustainability," *California Management Review*, vol. 57, no. 1, pp. 88–116, 2014.

[18] Y. S. Chen, "The positive effect of green intellectual capital on competitive advantages of firms," *Journal of Business Ethics*, vol. 77, no. 3, pp. 271–286, 2007.

[19] C. J. Chen and J. W. Huang, "Strategic human resource practices and innovation performance - the mediating role of knowledge management capacity," *Journal of Business Research*, vol. 62, no. 1, pp. 104–114, 2009.

[20] Y. S. Chen and C. H. Chang, "Utilize structural equation modeling (SEM) to explore the influence of corporate environmental ethics: the mediation effect of green human capital," *Quality and Quantity*, vol. 47, no. 1, pp. 79–95, 2013.

[21] E. Claver-Cortés, M. Dolores López-Gamero, J. F. Molina-Azorín, and P. Del Carmen Zaragoza-Sáez, "Intellectual and environmental capital," *Journal of Intellectual Capital*, vol. 8, no. 1, pp. 171–182, 2007.

[22] S. Sharma and J. Aragón-Correa, *Corporate Environmental Strategy and Competitive Advantage*, Edward Elgar, Cheltenham, U.K.; North Hampton, MA, 2005.

[23] N. Soewarno, B. Tjahjadi, and F. Fithrianti, "Green innovation strategy and green innovation," *Management Decision*, vol. 57, no. 11, pp. 3061–3078, 2019.

[24] T. Davenport and L. Prusak, *Working Knowledge: How Organizations Manage what They Know*, Harvard Business Press, Cambridge, MA, 1998.

[25] J. Y. Yong, M. Y. Yusliza, T. Ramayah, and O. Fawehinmi, "Nexus between green intellectual capital and green human resource management," *Journal of Cleaner Production*, vol. 215, pp. 364–374, 2019.

[26] S. L. Hart, "A natural-resource-based view of the firm," *Academy of Management Review*, vol. 20, no. 4, pp. 986–1014, 1995.

[27] S. L. Hart and G. Dowell, "Invited editorial: a natural-resource-based view of the firm," *Journal of Management*, vol. 37, no. 5, pp. 1464–1479, 2011.

[28] M. V. Russo and P. A. Fouts, "A resource-based perspective on corporate environmental performance and profitability," *Academy of Management Journal*, vol. 40, no. 3, pp. 534–559, 1997.

[29] J. A. Aragón-Correa and S. Sharma, "A contingent resource-based view of proactive corporate environmental strategy," *Academy of Management Review*, vol. 28, no. 1, p. 71, 2003.

[30] Y. M. Yusoff, M. K. Omar, M. D. Kamarul Zaman, and S. Samad, "Do all elements of green intellectual capital contribute toward business sustainability? Evidence from the Malaysian context using the Partial Least Squares method," *Journal of Cleaner Production*, vol. 234, pp. 626–637, 2019.

[31] J. Y. Yong, M. Y. Yusliza, C. J. C. Jabbour, and N. H. Ahmad, "Exploratory cases on the interplay between green human resource management and advanced green manufacturing in light of the Ability-Motivation-Opportunity theory," *The Journal of Management Development*, vol. 39, no. 1, pp. 31–49, 2019.

[32] G. Martín-de-Castro, M. Delgado-Verde, P. López-Sáez, and J. E. Navas-López, "Towards 'an intellectual capital-based view of the firm': origins and nature," *Journal of Business Ethics*, vol. 98, no. 4, pp. 649–662, 2010.

[33] K. K. Reed, M. Lubatkin, and N. Srinivasan, "Proposing and testing an intellectual capital-based view of the firm," *Journal of Management Studies*, vol. 43, no. 4, pp. 867–893, 2006.

[34] J. Barney, "Firm resources and sustained competitive advantage," *Journal of Management*, vol. 17, no. 1, pp. 99–120, 1991.

[35] R. L. Priem and J. E. Butler, "Is the resource-based "view" a useful perspective for strategic management research?" *Academy of Management Review*, vol. 26, no. 1, pp. 22–40, 2001.

[36] N. J. Foss and T. Knudsen, "The resource-based tangle: towards a sustainable explanation of competitive advantage," *Managerial and Decision Economics*, vol. 24, no. 4, pp. 291–307, 2003.

[37] M. A. Youndt, M. Subramaniam, and S. A. Snell, "Intellectual capital profiles: an examination of investments and returns," *Journal of Management Studies*, vol. 41, no. 2, pp. 335–361, 2004.

[38] T. Andreeva, T. Garanina, J. Sáenz, N. Aramburu, and A. Kianto, "Does country environment matter in the relationship between intellectual capital and innovation performance?" *Journal of Business Research*, vol. 136, pp. 263–273, 2021.

[39] S. Y. Malik, Y. Cao, Y. H. Mughal, G. M. Kundi, M. H. Mughal, and T. Ramayah, "Pathways towards sustainability in organizations: empirical evidence on the role of green human resource management practices and green intellectual capital," *Sustainability*, vol. 12, no. 8, p. 3228, 2020.

[40] J. Jirakraisiri, Y. F. Badir, and B. Frank, "Translating green strategic intent into green process innovation performance: the role of green intellectual capital," *Journal of Intellectual Capital*, vol. 22, no. 7, pp. 43–67, 2021.

[41] V. T. Dang and J. Wang, "Building competitive advantage for hospitality companies: the roles of green innovation strategic orientation and green intellectual capital," *International Journal of Hospitality Management*, vol. 102, Article ID 103161, 2022.

[42] K. Haldorai, W. G. Kim, and R. F. Garcia, "Top management green commitment and green intellectual capital as enablers of hotel environmental performance: the mediating role of green human resource management," *Tourism Management*, vol. 88, Article ID 104431, 2022.

[43] C. Huang and F. Kung, "Environmental consciousness and intellectual capital management," *Management Decision*, vol. 49, no. 9, pp. 1405–1425, 2011.

[44] B. Marco-Lajara, P. Zaragoza-Saez, J. M. Martínez Falcó, and L. A. Millan-Tudela, "Analysing the relationship between green intellectual capital and the achievement of the sustainable development goals," in *Handbook of Research on Building Inclusive Global Knowledge Societies for Sustainable Development*, pp. 111–129, IGI Global, Hershey, Pennsylvania, 2022.

[45] Y. S. Chen, "The driver of green innovation and green image - green core competence," *Journal of Business Ethics*, vol. 81, no. 3, pp. 531–543, 2008.

[46] C. Liu, "Developing green intellectual capital in companies by AHP," in *Proceedings of the En 2010 8th International Conference On Supply Chain Management And Information*, pp. 1–5, IEEE, Hong Kong, China, October 2010.

[47] M. D. López-Gamero, P. Zaragoza-Sáez, E. Claver-Cortés, and J. F. Molina-Azorín, "Sustainable development and intangibles: building sustainable intellectual capital," *Business Strategy and the Environment*, vol. 20, no. 1, pp. 18–37, 2011.

[48] C. Chang and Y. Chen, "The determinants of green intellectual capital," *Management Decision*, vol. 50, no. 1, pp. 74–94, 2012.

[49] C. M. Jardon and A. Dasilva, "Intellectual capital and environmental concern in subsistence small businesses," *Management of Environmental Quality: An International Journal*, vol. 28, no. 2, pp. 214–230, 2017.

[50] S. Anik and H. Sulistyo, "The role of green intellectual capital and green innovation on competitive advantage of SMEs," *International Journal of Learning and Intellectual Capital*, vol. 1, no. 1, p. 1, 2020.

[51] Y. S. Chen, S. B. Lai, and C. T. Wen, "The influence of green innovation performance on corporate advantage in Taiwan," *Journal of Business Ethics*, vol. 67, no. 4, pp. 331–339, 2006.

[52] R. J. Lin, K. H. Tan, and Y. Geng, "Market demand, green product innovation, and firm performance: evidence from Vietnam motorcycle industry," *Journal of Cleaner Production*, vol. 40, pp. 101–107, 2013.

[53] P. Kivimaa and P. Kautto, "Making or breaking environmental innovation?" *Management Research Review*, vol. 33, no. 4, pp. 289–305, 2010.

[54] J. Salvadó, G. De Castro, M. Verde, and J. López, *Environmental Innovation and Firm Performance: A Natural Resource-Based View*, Palgrave Macmillan, London, United Kingdom, 2012.

[55] G. Albort-Morant, A. Leal-Millán, and G. Cepeda-Carrión, "The antecedents of green innovation performance: a model of learning and capabilities," *Journal of Business Research*, vol. 69, no. 11, pp. 4912–4917, 2016.

[56] A. Pipatprapa, H. H. Huang, and C. H. Huang, "The role of quality management & innovativeness on green performance," *Corporate Social Responsibility and Environmental Management*, vol. 24, no. 3, pp. 249–260, 2017.

[57] Y. Zhang, J. Sun, Z. Yang, and Y. Wang, "Critical success factors of green innovation: technology, organization and environment readiness," *Journal of Cleaner Production*, vol. 264, Article ID 121701, 2020.

[58] A. Mansoor, S. Jahan, and M. Riaz, "Does green intellectual capital spur corporate environmental performance through green workforce?" *Journal of Intellectual Capital*, vol. 22, no. 5, pp. 823–839, 2021.

[59] S. M. Allameh, "Antecedents and consequences of intellectual capital," *Journal of Intellectual Capital*, vol. 19, no. 5, pp. 858–874, 2018.

[60] Y. M. Yusoff, M. Nejati, D. M. H. Kee, and A. Amran, "Linking green human resource management practices to environmental performance in hotel industry," *Global Business Review*, vol. 21, no. 3, pp. 663–680, 2020.

[61] C. H. Wang and W. Juo, "An environmental policy of green intellectual capital: green innovation strategy for performance sustainability," *Business Strategy and the Environment*, vol. 30, no. 7, pp. 3241–3254, 2021.

[62] C. Pellegrini, F. Rizzi, and M. Frey, "The role of sustainable human resource practices in influencing employee behavior for corporate sustainability," *Business Strategy and the Environment*, vol. 27, no. 8, pp. 1221–1232, 2018.

[63] J. Xu and Y. Zhang, "Exploring the nonlinear effect of intellectual capital on financial performance: evidence from listed shipping companies in China," *Complexity*, vol. 2021, pp. 1–12, 2021.

[64] S. A. Yawar and S. Seuring, "Management of social issues in supply chains: a literature review exploring social issues, actions and performance outcomes," *Journal of Business Ethics*, vol. 141, no. 3, pp. 621–643, 2017.

[65] M. Kohtamäki, J. Vesalainen, S. Henneberg, P. Naudé, and M. J. Ventresca, "Enabling relationship structures and relationship performance improvement: the moderating role of relational capital," *Industrial Marketing Management*, vol. 41, no. 8, pp. 1298–1309, 2012.

[66] M.-Y. Yusliza, J. Y. Yong, M. I. Tanveer, T. Ramayah, J. Noor Faezah, and Z. Muhammad, "A structural model of the impact of green intellectual capital on sustainable

performance," *Journal of Cleaner Production*, vol. 249, Article ID 119334, 2020.

[67] V. Matinaro, Y. Liu, T. R. J. S. Lee, J. Poesche, and J. Poesche, "Extracting key factors for sustainable development of enterprises: case study of SMEs in Taiwan," *Journal of Cleaner Production*, vol. 209, pp. 1152–1169, 2019.

[68] Y. Yu and B. Huo, "The impact of environmental orientation on supplier green management and financial performance: the moderating role of relational capital," *Journal of Cleaner Production*, vol. 211, pp. 628–639, 2019.

[69] B. Marco-Lajara, P. Zaragoza-Sáez, J. Martínez-Falcó, and E. Sánchez-García, "Green intellectual capital in the Spanish wine industry," in *Innovative Economic, Social, and Environmental Practices for Progressing Future Sustainability*, pp. 102–120, IGI global, Practice, Progress, and Proficiency in Sustainability, Spain, 2022.

[70] M. Gürlek and M. Tuna, "Reinforcing competitive advantage through green organizational culture and green innovation," *Service Industries Journal*, vol. 38, no. 7-8, pp. 467–491, 2018.

[71] C. H. Wang, "How organizational green culture influences green performance and competitive advantage," *Journal of Manufacturing Technology Management*, vol. 30, no. 4, pp. 666–683, 2019.

[72] S. P. Chuang and S. J. Huang, "The effect of environmental corporate social responsibility on environmental performance and business competitiveness: the mediation of green information technology capital," *Journal of Business Ethics*, vol. 150, no. 4, pp. 991–1009, 2018.

[73] M. Buenechea-Elberdin, J. Sáenz, and A. Kianto, "Knowledge management strategies, intellectual capital, and innovation performance: a comparison between high- and low-tech firms," *Journal of Knowledge Management*, vol. 22, no. 8, pp. 1757–1781, 2018.

[74] J. Xu, Y. Shang, W. Yu, and F. Liu, "Intellectual capital, technological innovation and firm performance: evidence from China's manufacturing sector," *Sustainability*, vol. 11, no. 19, p. 5328, 2019.

[75] A. Alrowwad, S. H. AbualoushAbualoush, and R. Masa'deh, "Innovation and intellectual capital as intermediary variables among transformational leadership, transactional leadership, and organizational performance," *The Journal of Management Development*, vol. 39, no. 2, pp. 196–222, 2020.

[76] S. Liu, Q. Yu, L. Zhang, J. Xu, and Z. Jin, "Does intellectual capital investment improve financial competitiveness and green innovation performance? Evidence from renewable energy companies in China," *Mathematical Problems in Engineering*, vol. 2021, Article ID 9929202, pp. 1–13, 2021.

[77] H. Ullah, Z. Wang, M. Mohsin, W. Jiang, and H. Abbas, "Multidimensional perspective of green financial innovation between green intellectual capital on sustainable business: the case of Pakistan," *Environmental Science and Pollution Research*, vol. 29, no. 4, pp. 5552–5568, 2022.

[78] M. Subramaniam and M. A. Youndt, "The influence of intellectual capital on the types of innovative capabilities," *Academy of Management Journal*, vol. 48, no. 3, pp. 450–463, 2005.

[79] T. Li, L. Liang, and D. Han, "Research on the efficiency of green technology innovation in China's provincial high-end manufacturing industry based on the Raga-PP-SFA model," *Mathematical Problems in Engineering*, vol. 2018, Article ID 9463707, pp. 1–13, 2018.

[80] M. Ahmad and N. Ahmed, "Testing the relationship between intellectual capital and a firm's performance: an empirical investigation regarding financial industries of Pakistan," *International Journal of Learning and Intellectual Capital*, vol. 13, no. 2/3, p. 250, 2016.

[81] P. Moran, "Structural vs. relational embeddedness: social capital and managerial performance," *Strategic Management Journal*, vol. 26, no. 12, pp. 1129–1151, 2005.

[82] J. Huang and Y. Li, "The mediating effect of knowledge management on social interaction and innovation performance," *International Journal of Manpower*, vol. 30, no. 3, pp. 285–301, 2009.

[83] P. C. ChenChen and S. W. HungHung, "Collaborative green innovation in emerging countries: a social capital perspective," *International Journal of Operations & Production Management*, vol. 34, no. 3, pp. 347–363, 2014.

[84] D. Ryu, K. H. Baek, and J. Yoon, "Open Innovation with relational capital, technological innovation capital, and international performance in SMEs," *Sustainability*, vol. 13, no. 6, p. 3418, 2021.

[85] N. Thi Mai Anh, L. Hui, V. D. Khoa, and S. Mehmood, "Relational capital and supply chain collaboration for radical and incremental innovation," *Asia Pacific Journal of Marketing & Logistics*, vol. 31, no. 4, pp. 1076–1094, 2019.

[86] O. Boiral, "Tacit knowledge and environmental management," *Long Range Planning*, vol. 35, no. 3, pp. 291–317, 2002.

[87] P. Dickel, J. Hörisch, and T. Ritter, "Networking for the environment: the impact of environmental orientation on start-ups' networking frequency and network size," *Journal of Cleaner Production*, vol. 179, pp. 308–316, 2018.

[88] L. Cinquini, E. Passetti, A. Tenucci, and M. Frey, "Analyzing intellectual capital information in sustainability reports: some empirical evidence," *Journal of Intellectual Capital*, vol. 13, no. 4, pp. 531–561, 2012.

[89] N. Aramburu and J. Sáenz, "Structural capital, innovation capability, and size effect: an empirical study," *Journal of Management and Organization*, vol. 17, no. 3, pp. 307–325, 2011.

[90] I. Maurer, V. Bartsch, and M. Ebers, "The value of intra-organizational social capital: how it fosters knowledge transfer, innovation performance, and growth," *Organization Studies*, vol. 32, no. 2, pp. 157–185, 2011.

[91] J. J. García-Machado and M. Martínez-Avila, "Environmental performance and green culture: the mediating effect of green innovation. An application to the automotive industry," *Sustainability*, vol. 11, no. 18, p. 4874, 2019.

[92] H. H. Weng, J. S. Chen, and P. C. Chen, "Effects of green innovation on environmental and corporate performance: a stakeholder perspective," *Sustainability*, vol. 7, no. 5, pp. 4997–5026, 2015.

[93] D. Kammerer, "The effects of customer benefit and regulation on environmental product innovation," *Ecological Economics*, vol. 68, no. 8-9, pp. 2285–2295, 2009.

[94] A. Adegbile, D. Sarpong, and D. Meissner, "Strategic foresight for innovation management: a review and research agenda," *International Journal of Innovation and Technology Management*, vol. 14, no. 04, Article ID 1750019, 2017.

[95] J. Zhang, G. Liang, T. Feng, C. Yuan, and W. Jiang, "Green innovation to respond to environmental regulation: how external knowledge adoption and green absorptive capacity matter?" *Business Strategy and the Environment*, vol. 29, no. 1, pp. 39–53, 2020.

[96] W. Ben Arfi, L. Hikkerova, and J. M. Sahut, "External knowledge sources, green innovation and performance," *Technological Forecasting and Social Change*, vol. 129, pp. 210–220, 2018.

[97] K. H. Lee and B. Min, "Green R&D for eco-innovation and its impact on carbon emissions and firm performance," *Journal of Cleaner Production*, vol. 108, pp. 534–542, 2015.

[98] J. Conding, N. Habidin, A. Zubir, S. Hashim, and N. Jaya, "The structural analysis of green innovation (GI) and green performance (GP) in Malaysian automotive industry," *Research Journal of Finance and Accounting*, vol. 3, no. 6, pp. 172–178, 2012.

[99] S. Kraus, S. U. Rehman, and F. J. S. García, "Corporate social responsibility and environmental performance: the mediating role of environmental strategy and green innovation," *Technological Forecasting and Social Change*, vol. 160, Article ID 120262, 2020.

[100] T. Y. Chiou, H. K. Chan, F. Lettice, and S. H. Chung, "The influence of greening the suppliers and green innovation on environmental performance and competitive advantage in Taiwan," *Transportation Research Part E: Logistics and Transportation Review*, vol. 47, no. 6, pp. 822–836, 2011.

[101] Q. Zhu and J. Sarkis, "Relationships between operational practices and performance among early adopters of green supply chain management practices in Chinese manufacturing enterprises," *Journal of Operations Management*, vol. 22, no. 3, pp. 265–289, 2004.

[102] N. A. Abu Seman, N. Zakuan, A. Jusoh, M. Arif, and M. Saman, "Green supply chain management: a review and research direction," *International Journal of Managing Value and Supply Chains*, vol. 3, no. 1, pp. 1–18, 2012.

[103] Y. Huang and Y. Jim Wu, "The effects of organizational factors on green new product success," *Management Decision*, vol. 48, no. 10, pp. 1539–1567, 2010.

[104] Y. Dong, X. Wang, J. Jin, Y. Qiao, and L. Shi, "Effects of eco-innovation typology on its performance: empirical evidence from Chinese enterprises," *Journal of Engineering and Technology Management*, vol. 34, pp. 78–98, 2014.

[105] T. M. Welbourne and M. Pardo-del-Val, "Relational capital: strategic advantage for small and medium-size enterprises (SMEs) through negotiation and collaboration," *Group Decision and Negotiation*, vol. 18, no. 5, pp. 483–497, 2009.

[106] B. Roxas, M. Battisti, and D. Deakins, "Learning, innovation and firm performance: knowledge management in small firms," *Knowledge Management Research and Practice*, vol. 12, no. 4, pp. 443–453, 2014.

[107] L. Fleming and O. Sorenson, "Science as a map in technological search," *Strategic Management Journal*, vol. 25, no. 89, pp. 909–928, 2004.

[108] C. Meyer, B. Skaggs, and M. Youndt, "Developing and deploying organizational capital in services vs. manufacturing," *Journal of Managerial Issues*, vol. 26, no. 4, pp. 326–344, 2014.

[109] M. Delgado-Verde, J. Amores-Salvadó, G. Martín-de Castro, and J. E. Navas-López, "Green intellectual capital and environmental product innovation: the mediating role of green social capital," *Knowledge Management Research and Practice*, vol. 12, no. 3, pp. 261–275, 2014.

[110] E. Giuliani, "The selective nature of knowledge networks in clusters: evidence from the wine industry," *Journal of Economic Geography*, vol. 7, no. 2, pp. 139–168, 2007.

[111] S. Turner, "Networks of learning within the English wine industry," *Journal of Economic Geography*, vol. 10, no. 5, pp. 685–715, 2010.

[112] L. Cassi, A. Morrison, and A. L. Ter Wal, "The evolution of trade and scientific collaboration networks in the global wine sector: a longitudinal study using network analysis," *Economic Geography*, vol. 88, no. 3, pp. 311–334, 2012.

[113] G. Cepeda-Carrion, J. G. Cegarra-Navarro, and V. Cillo, "Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management," *Journal of Knowledge Management*, vol. 23, no. 1, pp. 67–89, 2019.

[114] P. Paillé, Y. Chen, O. Boiral, and J. Jin, "The impact of human resource management on environmental performance: an employee-level study," *Journal of Business Ethics*, vol. 121, no. 3, pp. 451–466, 2014.

[115] W. S. Chow and Y. Chen, "Corporate sustainable development: testing a new scale based on the mainland Chinese context," *Journal of Business Ethics*, vol. 105, no. 4, pp. 519–533, 2012.

[116] E. Ocde, "Manual de Oslo: Guía para la recogida e interpretación de datos sobreinnovación," 2005, http://www.itq.edu.mx/convocatorias/manualdeoslo.pdf.

[117] J. Roldan and G. Cepeda, *Modelos de Ecuaciones basados en la Varianza: PartialLeast Squares (PLS) para Investigadores en Ciencias Sociales*, Universidad de Sevilla, Sevilla, Andalucía, Spain, 2017.

[118] J. F. Hair, M. Sarstedt, and C. M. Ringle, "Rethinking some of the rethinking of partial least squares," *European Journal of Marketing*, vol. 53, no. 4, pp. 566–584, 2019.

[119] F. Ali, S. M. Rasoolimanesh, M. Sarstedt, C. M. Ringle, and K. Ryu, "An assessment of the use of partial least squares structural equation modeling (PLS-SEM) in hospitality research," *International Journal of Contemporary Hospitality Management*, vol. 30, no. 1, pp. 514–538, 2018.

[120] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115–135, 2015.

[121] W. Reinartz, M. Haenlein, and J. Henseler, "An empirical comparison of the efficacy of covariance-based and variance-based SEM," *International Journal of Research in Marketing*, vol. 26, no. 4, pp. 332–344, 2009.

[122] J. Henseler, G. Hubona, and P. A. Ray, "Using PLS path modeling in new technology research: updated guidelines," *Industrial Management & Data Systems*, vol. 116, no. 1, pp. 2–20, 2016.

[123] L. T. Hu and P. M. Bentler, "Fit indices in covariance structure modeling: sensitivity to underparameterized model misspecification," *Psychological Methods*, vol. 3, no. 4, pp. 424–453, 1998.

[124] B. Byrne, *Structural Equation Modeling with EQS: Basic Concepts, Applications, and Programming*, Psychology Press, New York, United States, 2008.

[125] E. G. Carmines and R. A. Zeller, *Reliability and validity assessment*, vol. 17, Sage, Newcastle upon Tyne, United Kingdom, 1979.

[126] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981.

[127] R. Kline, *Principles and Practice of Structural Equation Modeling*, Guilford Press, New York, N Y, USA, 2011.

[128] J. Hair, G. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage publications, Newcastle upon Tyne, United Kingdom, 2016.

[129] A. Gilinsky, S. K. Newton, and R. F Vega, "Sustainability in the global wine industry: concepts and cases," *Agriculture and Agricultural Science Procedia*, vol. 8, pp. 37–49, 2016.

[130] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, Routledge, New York, NY, USA, 1988.

[131] C. H. Chang, "The determinants of green product innovation performance," *Corporate Social Responsibility and Environmental Management*, vol. 23, no. 2, pp. 65–76, 2016.
[132] M. Hertsgaard, "What climate change means for wine industry," *Wired Science*, vol. 26, pp. 2011–2023, 2010.
[133] E. Annunziata, T. Pucci, M. Frey, and L. Zanni, "The role of organizational capabilities in attaining corporate sustainability practices and economic performance: evidence from Italian wine industry," *Journal of Cleaner Production*, vol. 171, pp. 1300–1311, 2018.
[134] J. Á. del Bríodel Brío, E. Fernández, and B. Junquera, "Management and employee involvement in achieving an environmental action-based competitive advantage: an empirical study," *International Journal of Human Resource Management*, vol. 18, no. 4, pp. 491–522, 2007.
[135] P. C. Zaragoza-Sáez, E. Claver-Cortés, B. Marco-Lajara, and M. Úbeda-García, "Corporate social responsibility and strategic knowledge management as mediators between sustainable intangible capital and hotel performance," *Journal of Sustainable Tourism*, pp. 1–23, 2020.

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Research Article

The Complexity of Interaction between Executive Board Gender Diversity and Financial Performance: A Panel Analysis Approach Based on Random Effects

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This study examined the influence of the executive board of directors' gender diversity on the financial performance of listed companies on the Bucharest Stock Exchange, for the period 2011 to 2019. The analysis of the composition and different characteristics of the board and the executive directors proved to be effective tools for corporate governance in countries with an emerging capital market. Therefore, a disclosure index on directors' characteristics was used to moderate the interaction between gender diversity and financial performance, based on the theoretical framework provided by upper echelon theory. The study contributes to the enrichment of the literature both by using the composite indicator built by applying the multiway PCA method on panel data to express financial performance and by designing the ten EGLS panel models involving five financial indicators and two proxies for gender diversity. The results showed that there is a positive impact of the proportion of women on the executive board of directors on financial performance, measured through the composite index, ROA, ROE, and SOL. A statistically significant impact of gender diversity on financial performance was found only for SOL, in the case of the Blau index. Also, using the random-effects model to perform the panel data analysis, the results showed that a higher executive board size can be associated with better financial performance measured through the composite index, ROA, ROE, and EPS. Practical implications are significant for the board of executives' composition, the complexity of the relationship with the board, and reshaping governance practices.

1. Introduction

Diversity in the board and various senior management structures of entities is today one of the intensely debated and investigated topics. Among the aspects pursued both in practice and in research, gender diversity examined in correlation with various indicators of financial or nonfinancial performance occupies a central place and generates different research directions in the context of achieving the objectives of sustainability and sustainable development. Today, in the EU only 7.5% of chairpersons and 7.7% of CEOs are women. Consequently, it is necessary to take concrete action to increase the more balanced representation of women and men in decision-making roles, including the boards of directors and the management teams. About 33% of the executives' positions in Romanian publicly listed companies are occupied by women, according to Eurostat data for 2021 [1], and the share of female board executives was above the reported EU average. The National Strategy 2018–2021, adopted by the Romanian Government for the Promotion of Equal Opportunities and Treatment for Women and Men, included in the general objectives the encouragement of women's participation in decision-making, and between the major areas of intervention, the balanced participation in decision-making and gender mainstreaming. A recent study entitled Gender Economic Inequalities in Romania, published in late 2021 by Guga and Sindrestean [2], and conducted under Friedrich–Ebert–Stiftung Romania, showed that gender inequalities in Romania are among the largest in Europe.

Unfortunately, the situation has not improved significantly in the last decade, despite regulations adopted in recent years [3–5]. The study points out that in the labor market, women generally occupy inferior positions to men, being paid less and being more vulnerable to changes in business cycles. Despite significant economic growth and a theoretically very good economic period before the pandemic, women's participation in the labor market remained at very low levels, both compared with men and historically [2]. When it comes to the type of work performed by women, there are huge differences between the sectors of activity, and in the feminized sectors, the tendency is for women to occupy inferior positions to men.

Numerous empirical studies have shown that women can behave differently than men [6–10], being more open to collaboration, with more emphasis on morality and ethics, and a more participatory decision-making process, which leads to a reduction in management conflicts that improves the participatory decision-making process [11, 12]. Female directors are less thirsty for power, more diligent in overseeing and controlling certain processes, and more concerned with the quality of financial reporting [13, 14]. As Adams et al. [15] and Amin et al. [16] pointed out, from the perspective of investors the presence of women managers and their independence on the board are factors that enhance the future performance of the business. Elliott and Smith [6] showed that women on the board are more likely to push for more women to lead, and Adusei et al. [17] demonstrated the positive and statistically significant relationship between the board gender diversity and management gender diversity.

Board gender diversity refers to the presence of women on boards of directors [18, 19], whereas management gender diversity targets the female representation in the management team of companies [20, 21]. Terjesen and Singh [22] have shown that greater representation of women on boards increases the likelihood of women being represented in senior management and generates more equal proportions of salaries for men and women, whereas Adusei et al. [17] found that board gender diversity positively predicts management gender diversity and demonstrated that 50% or higher diversity in either board or management is the threshold at which gender diversity is productive to microfinance institutions. The former explains that a female representation of 50% or more, both in the board of directors and in the management committee, can result in a very high financial performance and conclude that too much pressure to increase female representation in the management of companies can have side effects and a lot of caution and tact is needed.

This study is consistent with the growing interest in examining gender diversity of boards and executive management structures in the context of sustainable business development and aimed to examine the impact of gender diversity and the size of the executive board of directors of selected listed companies on BSE, on financial performance. For this purpose, only companies that had continuity in the BSE listing for the period 2011–2019 and for which it was possible to collect and curate the data were included in the sample. We also considered several financial indicators and a composite one for the expression of performance and two proxies for gender diversity, the disclosure degree of characteristics related to CEOs was defined as the mediation variable, and the corporate governance report and audit report were used as control variables. To achieve these objectives, the study follows in the next section a brief description of the research theoretical framework, a structured review of corporate governance, gender diversity, and business performance prior works and the hypothesis development, Section 3 reports on the data, Sections 4 and 5 describe the general methodology and the way the performance composite index was designed, results were revealed and discussed in Section 6, and the last part of the study conclusions can be found and further research paths may be followed to continue developing the current research direction.

2. Literature Review and Hypothesis Development

The abundance of empirical studies on the impact of gender diversity on a company's performance shows that the interest of researchers and stakeholders in analyzing disclosed information about corporate governance is similar to that of financial information [23]. In this context, for the theoretical substantiation of the empirical study, our scientific approach to reviewing the most relevant papers follows a route that contains three stops. First, we stopped to select and briefly describe the main theories that can form the theoretical framework of empirical analysis, then we considered it necessary to briefly present a selection of works that focused on the analysis of Romanian corporate governance in relation or not to business performance, and in the last station of this section, we analyzed some of the previous studies that examined the correlation between gender diversity, size, the composition of board and management structures, and financial performance of companies to develop the research hypotheses.

2.1. Research Theoretical Framework/Theories

2.1.1. Agency Theory. Agency conflicts that arise in various organizations from the contractual relationship between principals and agents are the central concern of agency theory. Information asymmetry and incomplete contract information can create conflicts between owners and those mandated to run the business. From the perspective of this theory, the composition of boards has been analyzed extensively, often from an agency perspective, and focused on the characteristic of independence [24] and the idea that greater diversity in leadership positions can increase performance. The board of directors is a key governance device that can harmonize the interests of managers and owners, and it is important to note that higher agency costs that adversely affect the company's performance are frequently the result of poor governance [25]. As Hillman and Dalziel [26] pointed out, a fairly effective mechanism for reducing

agency costs is the independence of the board but also of gender diversity, justifying reasoning by the greater heterogeneity of opinions that can lead to more robust control over final decisions.

Gender diversity of the company's boards of directors, especially the personality traits of women directors who consider intolerant the opportunistic behavior of managers, violates the code and ethical principles, and they have a greater inclination towards quality communication and disclosure, and transparent governance reduces agency conflicts that exist from the separation of management and business owners [27–32]. Also, companies with a higher share of women on the boards of directors have proven to have more outstanding performance in terms of disclosure on corporate social responsibility practices, and fewer irregularities in financial reporting and fewer weaknesses and deficiencies in the internal control system can be found [33–36]. Women have a higher risk aversion when making financial decisions [7, 9, 37], and CEOs are directly involved in achieving goals and influencing financial reporting outcomes [38]. Francoeur et al. [8] point out that they have a more complex approach to situations and are more conscientious and cautious, traits that allow them to correct information biases in strategy formulation and problem-solving, whereas Francis et al. [39] showed the rise of accounting conservatism when a female director joins the management team.

2.1.2. Resource Dependence Theory. Resource dependence theory is one of the strongest theoretical justifications for the diversity of the board and management. The existence of diversity increases the likelihood that the information provided by the board to managers will be of high quality and prepared with high responsibility due to the unique information held by various directors. The company is perceived according to resource dependence theory as an open system permanently connected and shaped by changes in the external environment, whose goal is to reduce as much as possible dependence on limited resources, as Pfeffer and Salancik argued [40]. Thus, this theory becomes, through those established and emphasized by Pfeffer and Salancik [40], a framework for examining and understanding how boards of directors influence the performance of companies. In the opinion of Carter et al. [41], gender and ethnic differences will most likely produce unique categories of information available to management for better decision-making.

The extended resource dependence theory of Hillman et al. [42] suggested that different types of executives will provide different types of resources to companies. Moreover, women executives have certain relationship skills, and being more receptive to emotions and empathy, they gain certain advantages and more easily develop relationships with employed women but also with clients, and thus, in the opinion of the Liu et al. [43], a greater gender diversity improves business relationships. In the letter and spirit of the same theory, greater gender diversity means a stronger commitment to social responsibility, development of connections with stakeholders, and adoption of strategies to optimize the company's performance [44, 45]. Therefore, as an outcome, a more diverse board will assure more valuable resources that should produce better performance. Hillman et al. [46], Gabrielson and Huse [47], Peterson and Philpot [48], and Carter et al. [41] argued that due to human capital and different external links with the environment, women on board will not have the same effect on the board functions and company performance.

2.1.3. Upper Echelon Theory. Hambrick and Mason [49] emphasized that the essence of upper echelon theory is that managers make decisions and act in the development, review, and application of business strategies based on personalized interpretations of the situations, events, and circumstances they encounter. How the top management team influences the process of choices and strategic decisions at the level of the business organization that implicitly lead to different levels of financial performance is explained by upper echelon theory [49, 50]. Thus, the influence of women on boards on financial performance includes the direct impact of women on boards and the financial effects of corporate strategies that are estimated by the top management team [51]. Also, the study and analysis of the characteristics of the entire management team of the company will predict more accurately the organizational behavior on the performance line compared with the analysis only of the features of the executive managers.

The theoretical framework frequently used in previous studies to explain the connection between the presence of women on the board and the financial performance of companies refers to the upper echelon theory [52]. Behavioral differences between women and men directors are related to the essence of this theory and regardless of their psychological, cognitive nature, or system of values and beliefs will determine the characteristics of the boards and the executives' directors. Thus, women leaders care more about others by showing much empathy and a weaker desire for power, which may predict that a multi-women board and executive committee would seek to consider the interests of all stakeholders, which would lead to decisions harmonized with this behavior [13, 53]. Based on this theory, the group of executives should be more closely examined and analyzed because its members act as a bridge between the organization and the external environment and their choices and decisions are likely to influence the policies and strategies of performance and sustainable development [54–56]. Consequently, the architecture of the senior management team and its composition is expected to have a significant impact on strategic decisions; so, from the perspective of upper echelon theory, the traits and particularities of the executives' board deserve to be analyzed concerning the performance of the organization.

Another perspective on the same theory that considered various external environmental factors to the business organization, as well as the history of managers, is presented by Carpenter et al. [57] and involves an adjustment of the existing theory to the coordinates of the contemporary

business environment. The proposed model emphasizes the existing guidelines in research on the characteristics of top management related to organizational performance. The described model also introduces moderating and mediating variables as the central structure of the theory and takes into account the following: power, discretion, incentives, integration, and team processes. Thus, the results can be stratified according to the type of strategy and performance objectives pursued, with the analysis of system feedback.

2.2. Corporate Governance and Business Performance in Romania. Studies conducted on Romanian companies were initiated based on the analysis of the positive effects of the characteristics of the board of directors and executives on the performance of companies [11, 58–63], which proved that these are mainly generated by gender diversity, the duality of CEOs, and female CEOs. However, the results are not robust enough; in some works, they are even contradictory. Hence, among recent studies examining the influence of nonexecutive board members on the financial performance of Romanian companies listed on the BSE is Mihail and Micu's work [64], which analyzes the importance of directors' independence in corporate governance and shows that the higher share of independent board members is associated with a higher ROE indicator yield. Along with similar studies [23, 64–67] conducted on Romanian companies listed on BSE, our study is distinguished by (i) a more generous period covered by the analysis, 2011–2019, and the fragmented period before and after the transition to the international IFRS financial reporting framework; (ii) examining the link between the gender diversity of board executive managers and financial performance, the former expressed by 4 indicators (3 of profitability and one of liquidity), and also measured through a composite performance index; and (iii) measuring the average degree of disclosure of nonfinancial information about managers traits using scorecard variables.

Recent concerns of researchers related to the context of the Romanian business environment and companies are focused on the analysis of corporate governance or the influence of corporate governance on performance and in particular on financial performance [23, 68–72]. A significant effect of the Romanian corporate governance practices on the financial performance measured by ROE, EVA, and TSR cannot be proven, as Pintea et al. [68] found, but a significant and positive link was revealed in the case of the financial performance measured by Tobin's Q factor. Suciu et al. [53] in a dynamic comparative analysis aimed to examine how the gender diversity of boards of directors affects the financial performance of financial companies in France and Romania. The data analysis was performed between 2017 and 2019 on the sampled listed companies, using ROA and Tobin Q, to measure financial performance. Also, two metrics of female representation were used, the female proportion and the female presence for Romania, and the female presence at least equal to 40%, the quota imposed in the case of France. The results provide no evidence of a link between the gender diversity of boards of directors and the financial performance of companies.

Since 2016, companies listed on the BSE are required to disclose information on corporate governance through specific statements as proper reporting of governance practices significantly increases investor confidence [73]. The Corporate Governance Statement contains information on compliance with the provisions of the Corporate Governance Code and also presents an explanation of the deviations from them. BSE regularly monitors the degree of compliance with the provisions of the code by conducting regular surveys. Bogdan and Dumitrescu [69] in their investigation oriented on the analysis of the compliance degree with the Corporate Governance Code principles and provisions, of 61 listed companies on BSE, revealed that the total mean of the scores regarding the level of compliance is 77.14 points, out of 99, which can be interpreted as a fairly high degree of compliance with the corporate governance regulations. Concerned with the analysis of best practices in corporate governance in correlation with business performance, Achim et al. [23] in a study conducted on companies listed on BSE showed that there is a positive correlation between the quality of governance practices and the market value of companies. Their results proved to be robust only for one year, the correlation was found positive but not significant, and the performance was measured by Tobin's Q. The composition, structure, but also functions of the board of directors can vary from one country to another, from one governance model to another. On the other hand, it is relevant to mention that some countries have a unitary system of corporate governance, others have a dual system, and some, such as Romania, allow companies to choose between the two systems [53]. Most Romanian companies have opted for a two-tier model.

2.3. Gender Diversity and Financial Performance—Former Studies. Despite global efforts to achieve SDG5 targets, there is still a low level of representation of women in management positions in listed companies. However, Terjesen et al. [74] note that there is a significant gap in the representation of women on boards of directors, whereas Pucheta-Martínez [75] observed that developed countries adopt gender equality regulations to ensure greater participation of women in the management of organizations. Reguera-Alvarado et al. [24] analyzing the implications of Quota Laws on Spanish companies found that a higher representation of women on board is positively related to better financial results.

Several recent studies [8, 76–79] have shown that a higher number of women directors on board have an impact on corporate governance resulting in more responsible monitoring of business practices and more consistent encouragement of management to identify strategies to increase performance in the interest of shareholders. Even though some authors [18, 24, 32, 59, 80–84] consider that practices related to the integration of women in management positions can be an engine of improving the corporate governance of companies with a favorable impact on performance, others [85–89] demonstrate that the impact of board diversity on a company's financial performance can be

positive, negative, or neutral, depending on socioeconomic status, political characteristics, and cultural values of the analyzed country or region. In the case of emerging markets, other authors [90] considered that female managers only create value for companies when particularities of different sectors of activity are taken into consideration.

2.3.1. Board Size and Performance. Consequently, given the above, this study aimed to analyze the impact of gender diversity on the financial performance of Romanian companies listed on BSE, based on the theoretical framework provided by resource dependence, agency, and upper echelon theories. Gender diversity in our study considers the gender diversity of CEOs. Directors include the executive director, chief financial officer, human resource director, marketing and communication director, general manager, and other executive directors. So, in the study, we followed Carpenter's [54] and Papadakis and Barwise's [56] definition of top management teams and we included in our analysis the senior managers involved in the strategic decision-making and we focused our gender diversity investigation on CEOs. The management board regularly reports to the board of directors on all relevant aspects related to the activity, implementation strategy, risk profile, and risk management in the company. In addition, the management board ensures compliance with the provisions of the legislation in force regarding the capital market and its application by the company. The management board also ensures the implementation and operation of the accounting system, the risk management system, and the internal control system, which meet the requirements of the company.

The relationship between the size of the board of directors and the financial performance of companies is explained by the theory of resource dependence [91]. Thus, proponents of this theory argue that a larger number of board members will lead to a greater accumulation of resources [92]. However, opinions are divided and so we find that some support the idea that larger councils are more likely to impact performance indicators favorably [93–97] and argue that smaller boards are more efficient and enhance the performance of companies. Based on these records from previous research and assuming the connection between the size of the boards of directors and that of the management team and the average size of the management board for Romanian companies, we expect that:

> H1: the size of the management board is positively associated with the financial performance of listed Romanian companies

2.3.2. Gender Diversity and Financial Performance. In the scientific endeavor, we took into account the premises provided by the Romanian governance system that offers less shareholder protection [98] being more oriented towards meeting the needs of stakeholders and studies conducted by Campbell and Mínguez-Vera [59], Carter et al. [18], Erhardt et al. [83], and Reguera-Alvarado et al. [24], which showed that the membership of the women's board of directors is positively correlated with the performance of the companies. Controversy over gender diversity in the management of organizations stems from issues of independence, monitoring, and control, diminished cohesion among members of management and poor interaction, and syncope in communication if women directors are under-represented [96, 99, 100]. The results obtained by Gordini and Rancati [101] highlighted that the presence of at least one woman on board does not, alone, impact the financial performance of the company, but also gender diversity on a board does have a positive and significant effect on the company's financial performance. The authors' opinion is that Italian listed companies should concentrate on finding the optimum balance between women and men on boards and not just on the presence of women in the highest positions on boards and management teams. In companies with weaker shareholder protection, gender diversity positively affects performance, but in well-run companies, additional monitoring has been shown to have a negative impact, as Adams and Ferreira [29] proved and found a negative relationship between gender diversity and Tobin's Q, as well as ROA. As Anderson et al. [102] noted, the impact of diversity on financial performance differs depending on the company characteristics, and the diversity of the board of directors positively influences the performance of more complex companies but negatively impacts less complex organizations. Not only do the characteristics of the companies matter but also the business and social-cultural environment. Thus, in an analysis performed on Italian listed companies Rossi et al. [103] showed that there is a significant positive relationship between financial performance and the composition of the board, but in the study considering Polish listed companies, Kompa and Witkowska [104] observed that no significant correlation was found between the presence of women on board and ROE dynamics as an indicator of measuring financial performance.

The integration of women directors in the functioning of boards determines the increase in performance, as shown by Green and Homroy [105], but most studies estimate the effect of female representation and not participation, which may partially explain the neutral or negative impact on the company's performance of the representation of women on board. Green and Homroy [105] demonstrated a statistically positive and significant association between female representation and company performance, although the effect of the performance is modest. Thus, a change with a standard deviation of women's representation is equivalent to the entry of two women directors into the board, and the associated change in ROA is approximately 0.2%. Noja et al. [106] in their empirical study that used modeling structural equations and network analysis with Gaussian graphical models revealed that optimal board size, developed and improved management skills, greater participation of women in board leadership, and a structure at two-tier/levels of boards (a separate board of directors and a separate supervisory board) are significant management strategies that can facilitate the increase in financial performance indicators for companies and enhance the sustainable development of business. Our study followed Bennouri et al.

[107] work, which examined the relationship between female management, ROA, and ROE profitability indicators, for French companies, and showed that female management significantly increases profitability indicators for the analyzed companies.

In light of the above, we expect that:

H2: management board gender diversity has a significant impact on the financial performance composite index (FPindex)

H2a: management board gender diversity has a significant impact on EPS
H2b: management board gender diversity has a significant impact on ROA
H2c: management board gender diversity has a significant impact on ROE
H2d: management board gender diversity has a significant impact on SOL

3. Data Collection and Descriptive Statistics

Data were collected manually for the years 2011–2019 using the annual reports and financial statements of listed companies. We have selected 57 listed companies on the Bucharest Stock Exchange (BSE) according to the following criteria: online publication of annual reports and financial statements for the entire period, continuity of listing on the main market of BSE for the investigated period, and continuity of the activity in the same private sector of the economy. The total companies examined covered eight industries, from which 68.42% represent the manufacturing industry, and the others are companies in the trade, transport, and storage, construction, extractive, electricity and gas production, and professional and scientific-technical industries. Data on financial indicators were collected from the annual reports and refer to accounting-based profitability indicators, earnings per share (EPS), return on assets (ROA), return on equity (ROE), and a liquidity indicator, general solvency (SOL). The information collected on managers was also collected by reading the annual reports and looking for each year for the total number of managers, the distribution of managers by gender, and data on the number of male and female managers and scoring the disclosure degree on characteristics, such as studies, professional qualifications, work experience, training, previous managerial experience, complementary professional skills, and competencies, personality traits, and motivations, incentives, and bonuses.

As regarding executive managers' gender distribution in total selected listed companies, 75% of managers are male and 25% are female. The most balanced industries in terms of managers' gender distribution are the hospitality industry (51%–49%) and the professional, scientific, and technical activities (41%–59%), and the most unbalanced industry is the trade industry (97%–3%) (Figure 1).

If we analyze the evolution of gender distribution by industries from 2011 to 2019, we can observe that in the transport and storage industry an increase in the share of women managers is recorded from 16% in 2011 to 33% in 2019, and also, in the hotel and restaurant industry the increase in women managers in total is significant from 29% in 2011 to 46% in 2019. At the level of the most recent year analyzed, the following industries present extreme situations: in the construction industry and wholesale and retail trade industry, all reported managers are male, but in the professional, scientific, and technical activities the reported number of female managers is higher than male managers (71%). We also looked at the share of women managers in the total number of managers at the beginning and end of the period, and we found a 20% increase in the share of women managers in total, from 25% in 2011 to 30% in 2019 (see Figure 2).

The determination of the selected indicators for measuring the financial performance for the entire period was performed by own calculations using data collected from the annual reports of the analyzed companies. The most consistent source of data gathering was the financial statements included in the annual reports published on companies' websites. For all the nine years analyzed, the data on the selected financial indicators (EPS, ROA, ROE, and SOL) were centralized and verified, by companies and industries. Earnings per share (EPS) is among the most important indicators used when the aim is to determine a company's profitability on an absolute basis. The indicator expresses how much money a company earns for each share and is a widely used proxy for estimating corporate value. Thus, a higher EPS indicates a higher value, because investors will pay more for the shares of a company if they believe that the company has higher profits relating to the price of its shares. Earnings per share (EPS) was calculated by relating a company's net profit to the average number of its ordinary shares outstanding for the year reported. Therefore, we used the basic EPS indicator, following IAS 33. Return on assets (ROA) is another useful indicator for investors indicating how profitable a business relating to its assets, which is used by investors for a better understanding of a company's financial performance and strength. ROA is calculated by dividing a company's net profit by its total assets. Thus, if a company has a higher net profit than a competitor, it could claim that the company performs better. However, if the other company has a significantly higher ROA, that company uses its capital and assets more efficiently than the first company and may outperform it in the future. One of the most commonly used indicators for measuring financial performance is the return on equity (ROE). It is also one of the frequently selected indicators in studies that examine board management gender distribution of companies and financial performance. ROE is a measure of financial performance calculated by dividing net profit by equity, a financial expression of a corporation's profitability, and how effective it is in generating profits. The choice of the indicator regarding the global solvency (SOL), expressed as a ratio between the total assets and total liabilities, was made out of the desire to follow a liquidity indicator frequently used by Romanian companies. Therefore, the selection of financial indicators was made because they allow comparative analyses to be performed within the same industry for a certain period and

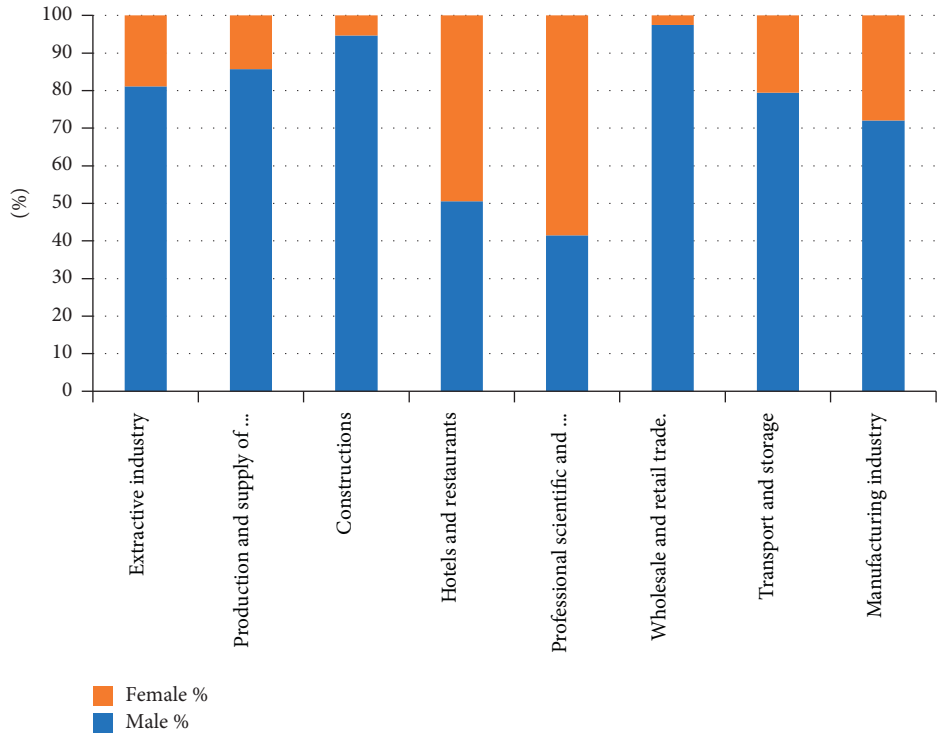

Figure 1: Managers' gender distribution by industries.

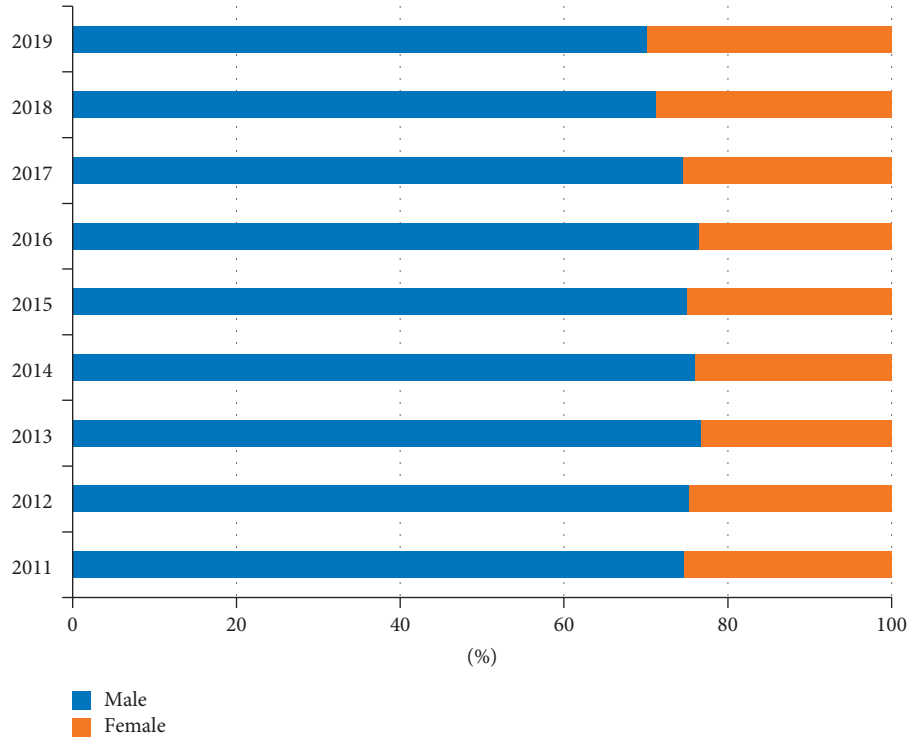

Figure 2: Evolution of managers' gender distribution in the period 2011–2019.

facilitate interpretation of the evolution of a company compared with competitors in the industry. The figure (Figure 3) shows the evolution of the average values of EPS, ROA, ROE, and SOL, by years and industries. The evolution of the financial performance indicators of sampled companies during the analyzed period 2011–2019 showed improvements after 2015. This favorable development can be explained by the advantages of applying the international financial reporting framework starting with 2013, for which the results are felt at the earliest next year.

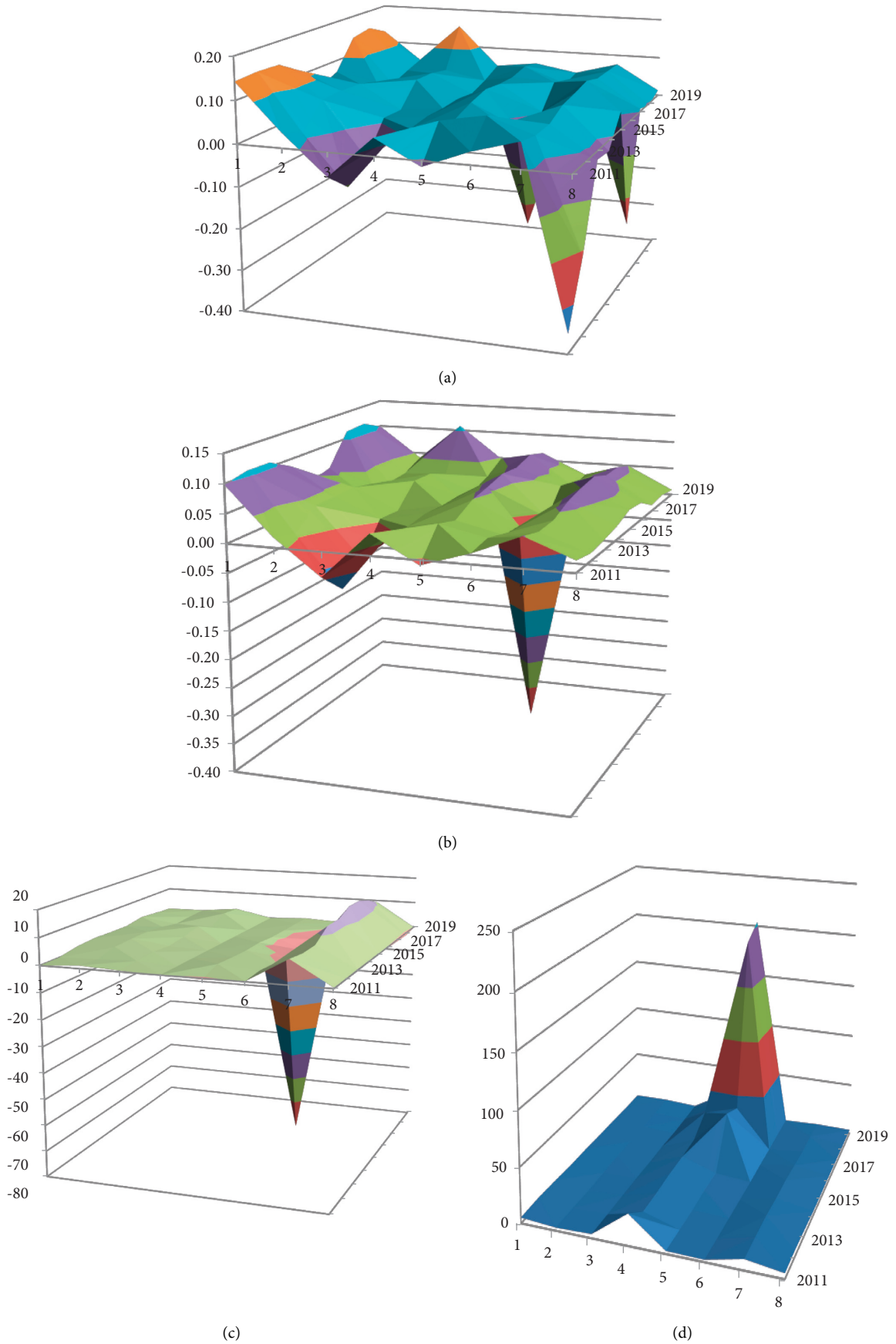

Figure 3: Mean of financial indicators for each industry, during the period 2011–2019. (a) ROE. (b) ROA. (c) EPS. (d) SOL.

4. Methodology

The paper aims to analyze the relationship between executive board gender diversity and financial performance and to examine the influence of gender diversity on performance, with a particular interest in measuring the disclosure index on specific managers' information and measuring the financial performance through a composite index. The study covered a sample of 57 companies listed at BSE grouped in eight industries, analyzed for the period 2011–2019. In line and consistent with previous studies, for financial performance, we have used 4 proxies: EPS, ROA, ROE, and SOL, and as a novelty, we designed a synthetic measure called the composite index of financial performance. To obtain such a composite measure, we have applied the multivariate principal component analysis (MPCA) method based on panel data. Brahma et al. [108] highlighted the advantages of using ROA as a proxy for financial performance, facilitating as shown above the comparisons between companies in the same industry and their classification according to the level of performance obtained in a weaker, good, or very good class. As recommended by Orlitzky et al. [109] and followed by Margolis et al. [110] and Wang et al. [111], ROE is employed as an alternate indicator of financial success. Therefore, using various techniques specific to panel data analysis, we have analyzed the effect of women's diversity on the financial performance of Romanian companies adding and using as an interaction variable, the disclosure index on managers' characteristics. For quantifying the extent of disclosure, the following score has been attributed: a score of 2 for detailed information, a score of 1.5 for existing but not detailed information, a score of 1 for poor information, and a score of 0 for no information.

Within the analysis, as already Arora [112] pointed out, board gender diversity is computed as the ratio of women directors dividing the total number of women directors by the total board size. As control variables, we have used two potential variables: the existence of an audit report for which the given score was 0 for no published report, score 1 for the opinion of other auditors than Big4, and score 2 for the opinion of Big4 auditors, and the existence of corporate governance report for which we have allocated score 0 for no report published, score 1 for one report published, and score 2 allocated for those cases where more information on governance than just one report was disclosed. The management board size was measured by the number of top manager members in the board executive management. According to Wang et al. [113], a large board can be more flexible and efficient and it is associated with fewer bureaucratic problems. Further on, we created two specific dummy variables: Big4 equals 1 if the firm audited their reports from Big4 otherwise equal to zero and detailed governance information equals 1 if there is more information on governance than just one report and 0 otherwise. We considered also industry dummy variables for each of the eight industries, having an industry as a benchmark to avoid dummy variable trap and year dummy variables for each year from 2011 to 2019. One-year dummy (2019) is treated as the benchmark to avoid the dummy variable trap. Starting from the observation of Arora [112], to examine the female board representation impact on companies' performance, the following model can be estimated:

$$FP_{it} = \beta_0 + \beta_1 \cdot RWD_{it} + \beta_2 \cdot BS_{it} + \sum_{j=1}^{2} \beta_j \cdot CV_{it} + \sum_{t=2011}^{2019} \gamma_t \cdot (\text{year})_t + \text{industrydummmies} + \mu_i + \varepsilon_{it}, \quad (1)$$

where RWD is the ratio of women managers on the board from the year 2011 to 2019; BS is the executives' board size, and as control variables (CV), we have considered the existence of audit reports and the existence of corporate governance reports; μ is unobserved fixed effect for the firm I, φ is assumed to be zero, and ε represents the remaining disturbance term.

The second model treating the effect of the disclosure index on managers' information on the financial performance of Romanian companies can be written as the following:

$$FP_{it} = \beta_0 + \beta_1 \cdot D\text{index}_{MNit} + \beta_2 \cdot BS_{it} + \sum_{j=1}^{2} \beta_j \cdot CV_{it} + \sum_{t=2011}^{2019} \gamma_t \cdot (\text{year})_t + \text{industrydummmies} + \mu_i + \varepsilon_{it}, \quad (2)$$

where Dindex_MN is the disclosure index on managers' information.

The robustness check relies on using an alternative measure of boardroom gender diversity (the Blau index) apart from the proportion of female managers and different measures for the company performance (the financial performance composite index, ROA, ROE, EPS, and SOL), and additionally, we have taken into account the firm size (measured by the natural log of total assets). To capture the interaction role (between women board diversity and financial performance of companies) of the disclosure index on managers' information, the following model has been developed:

$$FP_{it} = \beta_0 + \beta_1 \cdot D\text{index}_{MNit} + \beta_2 \cdot RWD_{it} + \beta_3 \cdot D\text{index\_}MN_{it} \cdot RWD_{it} + \beta_4 \cdot BS_{it} + \sum_{j=1}^{2} \beta_j \cdot CV_{it} + \sum_{t=2011}^{2019} \gamma_t \cdot (\text{year})_t + \text{industrydummmies} + \mu_i + \varepsilon_{it}, \quad (3)$$

where $D\text{index\_}MN \cdot RWD$ is the interaction term; i = observation (firm); and t = year of observation.

As potential robustness tests, we have used alternative measures of board gender diversity and alternative measures for the company performance and we have analyzed also the endogeneity problem. As observed by Brahma et al. [108], in

the literature that develops this topic of gender diversity in correlation with business performance, most empirical studies used three measures of gender diversity, namely percentage of female directors, gender dummy, and Blau index. According to Molla et al. [114], Blau's heterogeneity index is an appropriate measure of heterogeneity [115], but it is also the most favorable measure to capture diversification within a group of individuals in an organization [116]. The Blau index is the superior measure of board gender diversity if compared to the proportion of female directors [117]. Starting from the papers of Jiang et al. [118] and Wang et al. [113], the Blau index (BI) is computed as follows:

$$BI_i = 1 - \sum_{i=1}^{n} P_i^2, \tag{4}$$

where P_i is a percentage of women and men on the board and n is 2 describing the number of categories (women and male).

Multicollinearity refers to a high degree of correlation between independent variables, which can inflate regression findings [119]. The correlation matrix and variance inflation factor (VIF) can offer valuable information about the presence of multicollinearity. In the multiple regression model, for analyzing the panel data, the heteroscedasticity problem is a major concern, as it can invalidate the efficiency of statistical results [114, 120, 121]. Therefore, the statistical test of Breusch and Pagan [122] has been used to detect heteroscedasticity. Autocorrelation is the issue of error components being correlated across time due to high similarities. Further, a test for autocorrelation in panel data is used to detect serial or first-order autocorrelation. Cross-sectional dependence also known as contemporaneous correlation refers to the correlation of the residuals across entities. Pesaran's test is the appropriate test to explore whether the data have a cross-sectional dependence problem. Also, the Hausman test is employed to decide whether a fixed or random-effects model is suitable for this study. Table 1 summarizes the variables and measurements used in this study.

5. The Architecture of the Financial Performance Composite Index

One of the objectives pursued in the first stage of this work was the construction of the composite indicator to express financial performance and, in this respect, four ratios were considered: return on equity, return on assets, earnings per share, and overall solvency. For this purpose, the multiway PCA method was applied, which is a generalization of the main component analysis method, but applied to panel data. The empirical results showed the existence of two main components that recover using Kaiser's criterion, approximately 69% of the variant of financial indicators. Thus, if the first component recovers 44% of the original variable variant, the second component explains another 25%, both summing up 69% of the total variant (Table 2).

Based on the varimax method, the components were rotated to allow easy interpretation of components (Table 3). Thus, the first component is defined in terms of return on assets, whereas the second component can be defined in terms of global solvency.

The accuracy of the results is validated with the help of the Bartlett test and the Kaiser–Meyer–Olkin (KMO) statistics (Table 4), the results highlighting viable results.

Based on the variant recovered by each component, the total variant recovered as weights of the factor scores, and the nonstandard composite index of the financial performance of the companies during the period 2011–2019 is constructed as presented as follows:

$$Non_{std_{fin_{perf_{\text{index}}}}} = \frac{44}{69.05} * PC1 + \frac{25.04}{69.05} * PC2. \tag{5}$$

The final value given for each observation for each year is rescaled using the percentile rank. Thus, the financial performance index will indicate how a company performed in one year compared with another company in another year at its level. The index will take values between 0 (lowest financial performance) and 100 (highest financial performance). Therefore, a value of 50 represents an average level of financial performance.

Following the analysis of the financial performance index at the level of sampled companies in the period 2011–2019 (Figure 4), two clusters of companies can be observed: companies with good financial performance for the entire period (OMV Petrom, Turism Felix, Electrica, Conpet, Transgaz, SOCEP, Aerostar, Cemacon, IAR, Turbomecanica, Zentiva) and companies that marked performance improvements during the analyzed period (Electrica, Biofarm, Cemacon, IAR, Turbomecanica, Zentiva). Also, during the examined period (2011–2019), there are fluctuations in the average financial performance of selected companies, with increases in 2016 and 2018, but also decreases in 2017 and 2019, respectively (Figure 5).

Analyzing the average values of the composite financial performance index, we can conclude that the first placed companies in the top ranking by financial performance were occupied by Transgaz, Romgaz, Conpet, Biofarm, Casa de Bucovina-Club de Munte, and Zentiva, with scores over 80 points, whereas at the opposite pole Petrol export–import, Electroputere, and Armatura were situated, with average scores below 12 units.

6. Results and Discussion

Descriptive statistics of the dependent variable, the independent variables, the control variables, and the interaction variable used in this study are presented in Table 5. The dependent variable in our case is the financial performance of companies captured either individually using different indicators (ROE, ROA, EPS, or SOL) or in a synthetic manner through the designed composite index. The independent variable is the proportion of female managers and the disclosure index has an interaction role, whereas board size, disclosure of corporate governance, and audit reports are the control variables. Company financial performance measured through the synthetic indicator varies from low 0.19 to 100 with an average of 50.09. The average proportion

Table 1: Summary of variables.

Variables description	Abbreviation of variables	Measurement
Return on equity	ROE	Net profit/equity
Return on assets	ROA	Net profit/total assets
Earnings per share	EPS	Net profit/average number of ordinary shares outstanding for the reported year
Solvability	SOL	Total assets/total liabilities
Financial performance index	FP_index	Composite indicator built by applying MPCA based on panel data
Disclosure index	D_index	$DI_{\text{managers}} = \sum_{i=1}^{n} x_i/n$, where x_i = scores given according to the disclosure degree of the information on managers' characteristics and n = number of characteristics
Blau index	BI	$BI_i = 1 - \sum_{i=1}^{n} P_i^2$, where P_i is the percentage of women and men on the board and n is 2 describing the number of categories (women and men)
Women on board	RWD	The proportion of women on the executive board of directors
Board size	BS	Number of top executive managers on the management board
Corporate governance report	GOV_R	Publication of the governance report within the annual report of the analyzed companies
Audit report	Big4_R	Publication of the audit report prepared by Big4 within the annual report of the selected companies
Industry	Ind dummy	Industry dummy variables for each of the eight industries, having an industry as a benchmark to avoid dummy variable trap and year dummy variables for each year from 2011 to 2019.

Table 2: Total variance explained.

Comp.	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	1.760	44.008	44.008	1.760	44.008	44.008	1.751	43.773	43.773
2	1.002	25.049	69.057	1.002	25.049	69.057	1.011	25.285	69.057
3	0.910	22.760	91.817						
4	0.327	8.183	100.000						

Note. Extraction method: principal component analysis.

Table 3: Rotated component matrix.

	Component	
	1	2
Z score: earnings per share (EPS)	0.864	−0.079
Z score: return on assets (ROA)	0.904	0.034
Z score: return on equity (ROE)	0.433	0.268
Z score: global solvency (SOL)	0.006	0.966

Table 4: KMO and Bartlett's test.

Kaiser–Meyer–Olkin measure of sampling adequacy	0.511
Bartlett's test of sphericity approx. chi-square	327.965
df	6
Sig	0.000

of female managers is 0.25, whereas the Blau index varies from −0.0625 to 0.500, with an average of 0.218. The management board size ranges from 1 to 37, with an average of 5 members.

In Table 6, the correlation matrix is presented. For studying multicollinearity, an implicit assumption that is made when using the pooled regression method is that the explanatory variables are not correlated with one another. In effect, the correlation between explanatory variables will be nonzero; however, a problem occurs when the explanatory variables are very highly correlated with each other. By looking at the correlation matrix (Table 6), all correlation coefficients are lower than the threshold level of 0.5. Hence, no multicollinearity problem can affect findings.

In the statistical testing process, we used the ordinary least-squares method both cross section and period fixed-effects models for our estimations. The temporal effects included in the models were aimed at capturing, over time, the financial performance that is common to all Romanian companies. Testing of redundant fixed effects was used to decide which of these models is suitable for modeling our data set (fixed effects, periodic effects, cross-sectional effects, or both). The Hausman test was then used to identify whether a fixed-effects model (FEM) or a random-effects model (REM) is more appropriate. A low probability in the Hausman test suggests the use of fixed-effects models (FEMs), whereas a high probability in the test emphasizes REM (if there are reasons to assume that differences between entities have some influence on the dependent variable, then random effects should be used. Random effects assume that the entity's error term is not correlated with predictors that allow time-invariant variables to play a role of explanatory variables) (random-effects models). Cross-sectional dependence also known as contemporaneous correlation refers to the correlation of the residuals across entities. Therefore, Pesaran's test is the appropriate test to explore whether the

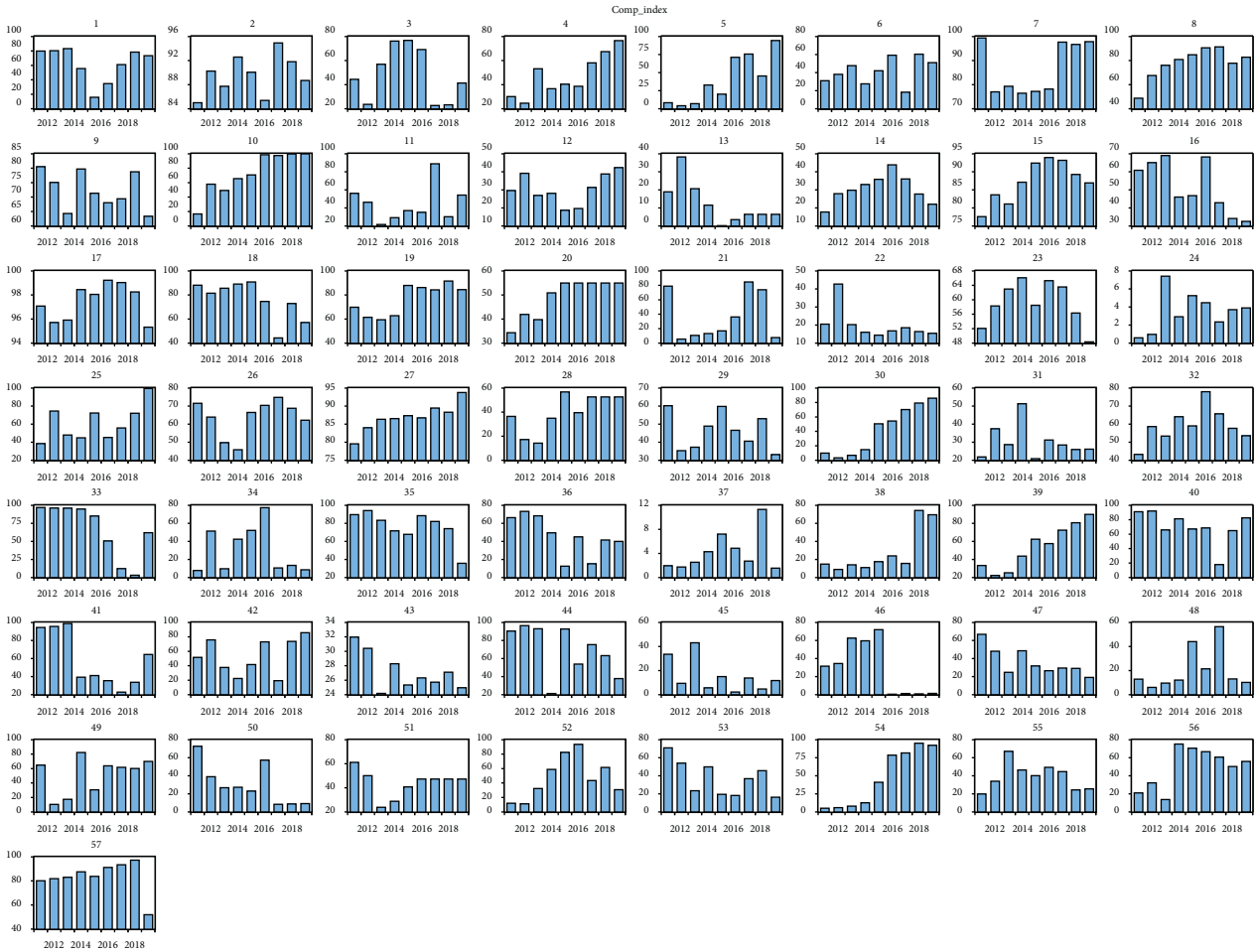

Figure 4: Performance composite index of each selected company.

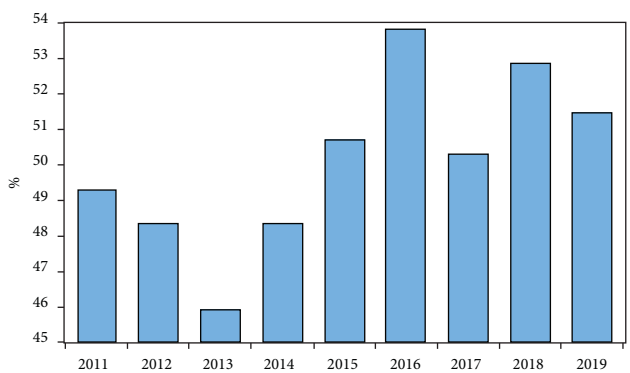

Figure 5: Composite index along the period 2011–2019.

data have a cross-sectional dependence problem. It is the most appropriate test for the panel data that have large cross-sectional units and small-time series [123]. The test is applied to the model and confirmed the existence of cross-sectional dependence in the model. The cross-sectional dependence was tested using three tests: Breusch–Pagan LM, Pesaran scaled LM, and Pesaran CD, whereas the homoscedasticity has been tested using the panel heteroscedasticity LR test, and the normality of residuals with the Jarque–Bera test. The type of model depends on the potential correlation of the explanatory variables with the unobservable effects (if the unobservable effects are uncorrelated with all the explanatory variables, it is recommended to use models with REM effects). The empirical results of the Hausman test together with the results of the Lagrange multiplier random-effects test showed that the random-effects estimator is consistent, with a probability very close to 1 in all specifications of our models. Therefore, different specifications of the model were estimated by assuming fixed effects, using the panel estimated generalized least-squares (EGLS) method.

The problem of cross-sectional heteroscedasticity was addressed using standard corrected heteroscedasticity errors based on the improvement of standard estimator errors, without changing the values of the coefficients. The Durbin–Watson statistics were used to test for the presence of residual autocorrelation. The goodness of fit of the models has been evaluated using adjusted R^2, root-mean-square error (RMSE), and the standard error of the model, whereas the validity of the models has been tested using the Fisher test. All proposed econometric models were estimated using the EViews 12 software package. However, the potential econometric problems of heteroscedasticity and cross-sectional dependence are found in the data. Random-effects

Table 5: Descriptive statistics.

	FPindex	ROE	ROA	EPS	SOL	PropFemMN	Blau index	D index	GOV R	AUD R	Board size
Mean	50.09741	−0.042579	0.023437	0.319117	5.822055	0.250853	0.218005	0.281433	1.265107	1.337232	4.920078
Median	50.10000	0.046100	0.027246	0.035700	3.132500	0.200000	0.244898	0.125000	1.000000	1.000000	4.000000
Maximum	100.0000	0.938900	0.905445	50.49880	204.1725	1.000000	0.500000	1.000000	2.000000	2.000000	37.00000
Minimum	0.190000	−12.00570	−1.468100	−281.6263	0.308003	0.000000	−0.062500	0.000000	0.000000	0.000000	1.000000
Std. Dev.	28.89586	0.771555	0.111884	13.77002	13.93999	0.278919	0.217600	0.315637	0.475874	0.505166	4.729339
Skewness	$1.65E-06$	−12.31542	−4.859498	−16.40757	10.92190	0.881731	0.102079	0.761310	0.620950	0.320571	3.779433
Kurtosis	1.800028	173.6248	77.48867	345.3846	145.0232	2.901986	1.186228	2.171000	2.452811	1.944077	22.30297
Obs.	513	513	513	513	513	513	513	513	513	513	513

models with heteroscedasticity cannot be efficiently estimated with ordinary least-squares (OLS). To solve the above issues, we have applied OLS with heteroscedastic panel-corrected standard errors (OLS-cross sectional panel-corrected standard errors—PCSEs). The estimator choice is based on the discussion provided by Molla et al. [114]. The PCSE estimate is robust not only to unit heteroscedasticity but also against possible contemporaneous correlation across the units [77, 124].

In Table 7, ten different models have been estimated using panel EGLS using five proxies for firm performance (ROA, ROE, EPS, SOL, and the composite index of financial performance) and two proxies for gender management board diversity (proportion of female managers and Blau's index). The empirical results pointed out a positive impact of the proportion of women on the executive board, leading to a better financial performance in four of five measures of financial performance (composite index, ROA, ROE, and SOL), with only the exception of EPS for which the result is insignificant. In the case of the second proxy of gender management board diversity, the Blau index, the impact is not so relevant, capturing only the statistically significant impact of gender diversity on financial performance only in the case of global solvability. The board size is found to be positively associated with most of the financial performance measures (composite index, ROA, ROE, and EPS), implying that a higher management board size can be associated with better firm performance. Also, the results of the impact of gender management board diversity on financial performance are presented in Table 6 testing hypothesis 2 with its components H2a to H2d, according to which the percentage of women in the executive board leads to better firm performance.

Further on, we followed the influence of board gender diversity on financial performance, given that the proportion of women on the executive board exceeds the 50% threshold. Thus, we have created a dummy variable considering the threshold of more than 50% of women proportion on the executive board and we have explored the influence of this variable on the financial performance of the companies. The empirical results presented in Table 8 highlighted that in most of the cases the impact continues to remain positive, pointing out that an overwhelming proportion of women managers increases the financial performance of the companies, except for the EPS indicator for which the impact is negative. A possible explanation for the negative impact that the majority proportion of women managers have on the financial performance of companies expressed by EPS would highlight the feature of women managers in Romania who are inclined towards less risky business strategies, more cautious behavior, and a tendency towards strengthening company status. However, looking at the situation from the perspective of the external environment, this result could express the lack of confidence of investors in the ability of women to make managerial decisions, where companies are predominantly led by women.

We can mention that female board diversity may lead to better accounting performance as suggested by Carter et al. [18], Erhardt et al. [83], Chen et al. [125], Kılıç and Kuzey [126], Arora [112], and Brahma et al. [108]. Therefore, putting together all information, the empirical results partially validated hypotheses H2, H2b, H2c, and H2d in the case of the proportion of female managers and invalidated the hypotheses H2, H2a, H2b, and H2c, in the case of Blau index. The hypothesis H2d is the only one that has been fully validated, confirming that management gender diversity captured by two proxies leads to a boost in the global solvability of the companies. Among control variables, audit report capturing if the company audited their reports from Big4 and detailed governance information, if there is more information on governance than just one report does not exhibit a common statistical impact, the effect being in most of the cases insignificant to conclude. However, from the few significant influences, we can point out a positive impact of Big4 on ROA and EPS leading to an increase in financial performance, as well as a negative impact of detailed governance information on the company performance.

Different measures of financial performance are positively correlated with the proportion of female directors on the board of executives. It indicates that having female executive directors on the board brings a variety of thinking to the table and that complicated circumstances may be handled more strategically with various skill sets, values and beliefs, and problem-solving abilities. This might be linked to increased board productivity and problem-solving abilities, resulting in improved corporate success. The findings also suggest that having more than one woman on a board of directors can improve a company's performance by bringing in a range of perspectives to the boardroom [112]. Also, the paper of Jiang et al. [118] confirmed that a female director has a positive effect on the company's financial performance being in line also with other studies reflecting a similar

Table 6: Correlation matrix.

	Correlation *t*-statistic										
Probability	Comp_index	ROE	ROA	EPS	SOL	Proportion of female MN	Blau index	Disclosure index	GOV R	Big4 R	Board size
FPindex	1.000000 — —										
ROE	0.287154 6.776593 0.0000	1.000000 — —									
ROA	0.600458 16.97421 0.0000	0.270508 6.351722 0.0000	1.000000 — —								
EPS	0.216443 5.011571 0.0000	0.118805 2.704789 0.0071	0.653260 19.50403 0.0000	1.000000 — —							
SOL	0.308530 7.332129 0.0000	0.040945 0.926361 0.3547	0.057245 1.296166 0.1955	0.018326 0.414345 0.6788	1.000000 — —						
Proportion of female MN	0.213855 4.948754 0.0000	0.077191 1.750137 0.0807	0.107147 2.436111 0.0152	0.035638 0.806119 0.4205	0.197575 4.556052 0.0000	1.000000 — —					
Blau index	0.163245 3.740367 0.0002	0.061417 1.390972 0.1648	0.069311 1.570581 0.1169	0.076494 1.734251 0.0835	0.126394 2.880281 0.0041	0.647608 19.21244 0.0000	1.000000 — —				
Disclosure index	0.035131 0.794630 0.4272	0.077769 1.763332 0.0784	0.105707 2.403009 0.0166	0.028737 0.649874 0.5161	0.043209 0.977671 0.3287	−0.042997 −0.972860 0.3311	0.000447 0.010108 0.9919	1.000000 — —			
GOV R	−0.070881 −1.606317 0.1088	−0.156265 −3.576365 0.0004	−0.052695 −1.192835 0.2335	−0.027142 −0.613784 0.5396	−0.084453 −1.915930 0.0559	0.089285 2.026415 0.0432	0.099236 2.254393 0.0246	0.062255 1.410024 0.1591	1.000000 — —		
Big4 R	0.077571 1.758817 0.0792	0.075761 1.717547 0.0865	0.153421 3.509691 0.0005	0.166042 3.806272 0.0002	−0.006305 −0.142521 0.8867	0.100101 2.274246 0.0234	0.121524 2.767598 0.0059	0.087271 1.980347 0.0482	0.098604 2.239895 0.0255	1.000000 — —	
Board size	0.319363 7.618261 0.0000	0.091396 2.074723 0.0385	0.193720 4.463668 0.0000	0.323505 7.728522 0.0000	0.016792 0.379634 0.7044	0.021985 0.497093 0.6193	0.186040 4.280225 0.0000	−0.018676 −0.422247 0.6730	−0.050448 −1.141843 0.2541	0.087332 1.981742 0.0480	1.000000 — —

Note. The table shows the correlations, the value of the *t*-test, and its probability.

Table 7: Impact of executive board gender diversity on financial performance using panel data analysis (random-effects model).

Models	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Robustness tests: alternative measures of management board gender diversity and alternative measures for firm performance										
Indep. Variables	Comp index	FPindex	ROE	ROA	EPS	SOL	ROE	ROA	EPS	SOL
Proportion of female MN	9.58*		0.179*	0.033*	1.09	11.81***				
Blau index		6.27					0.153	0.04	1.103	7.62*
Board size	0.98***	0.95***	0.0073*	0.003***	0.86***	0.125	0.007	0.003***	0.86***	0.09
Big4 R	2.41	2.56	0.087	0.02**	1.83**	−0.51	0.09	0.02	1.83**	−0.466
GOV R	−2.44	−2.72	−0.261**	−0.155	−0.54	−1.04	−0.26**	−0.015	−0.53	−1.07
Industry dummy	−12.45**		−0.097	−0.0003	0.141	−6.18**				−5.84
Constant	51.18***	43.86***	−0.016	−0.004	−4.82	6.94***	−0.07	−0.003	−4.65**	8.16***
Observations	513	513	513	513	513	513	513	513	513	513
F-test	3.56***	3.12**	2.58**	2.33**	7.03***	5.32***	2.85**	2.77**	8.91***	2.52***
S.E. of reg.	19.94	19.86	0.69	0.097	12.50	11.70	0.69	0.096	12.50	11.86
R^2	0.33	0.32	0.24	0.22	0.36	0.49	0.03	0.02	6.55	0.24
Jarque–Bera test	17.92 (0.00)	29.79 (0.00)	62.22 (0.00)	13.56 (0.00)	36.27 (0.00)	39.68 (0.00)	6.24 (0.00)	13.24 (0.00)	36.35 (0.00)	45.39 (0.00)
Random-effects Lagrange multiplier test	322.98 (0.000)	422.37 (0.00)	38.80 (0.00)	81.55 (0.00)	10.65 (0.00)	101.43 (0.00)	42.56 (0.00)	89.30 (0.00)	10.87 (0.00)	102.71 (0.00)
Hausman test prob.	0.156	0.1043	0.6686	0.78	0.4732	0.3048	0.7173	0.5467	0.4508	0.2334
Residual cross-sectional dependence test										
Breusch–Pagan LM test	2960.32 (0.00)	2877.62 (0.00)	2891.22 (0.00)	2558.86 (0.00)	2871.20 (0.00)	3382.34 (0.00)	2931.91 (0.00)	2575.12 (0.00)	2911.89 (0.00)	3222.52 (0.00)
Pesaran scaled LM test	24.14 (0.00)	22.68 (0.00)	22.92 (0.00)	17.02 (0.00)	22.57 (0.00)	31.61 (0.00)	23.64 (0.00)	17.33 (0.00)	23.29 (0.00)	27.78 (0.00)
Pesaran CD test	−0.47 (0.66)	−0.44 (065)	−0.76 (0.44)	0.61 (0.53)	−0.48 (0.62)	0.39 (0.69)	−0.82 (0.41)	0.75 (0.45)	−0.49 (0.61)	0.16 (0.86)
Panel cross-sectional heteroscedasticity LR test	135.84 (0.00)	149.41 (0.00)	2403.84 (0.00)	1006.06 (0.00)	4696.61 (0.00)	2140.25 (0.00)	2409.62 (0.00)	991.77 (0.00)	4660) (0.00)	2139.92 (0.00)

Note. ***, **, and * mean statistically significant at 1%, 5%, and 10%; () represents the probability.

Table 8: Impact of executive board gender diversity on financial performance when the proportion of women on board exceeds a threshold (over 50%).

Models	M1	M2	M3	M4	M5
Indep. variables	Comp index	ROE	ROA	EPS	SOL
Proportion of women managers ≥50%	6.85**	0.115**	0.0054	−0.639***	6.60***
Board size	1.07***	0.0096**	0.003***	0.83***	0.304*
Big4 R	1.57	−0.318***	−0.158	−32.23	7.26
GOV R	−1.36	−0.249**	−0.021***	33.36	0.292
Audit R	0.507	0.386***	0.173	−1.81***	−7.79**
Constant	43.41***	−0.211	−0.142	−4.82	9.98**
Observations	513	513	513	513	513
F-test	3.80***	2.69**	6.78**	20.90***	3.32***
S.E. of reg.	19.92	0.69	0.095	12.01	11.74
R^2	0.37	0.25	0.66	0.39	0.46
Jarque–Bera test	26.54 (0.00)	62.22 (0.00)	77.85 (0.00)	21.55 (0.00)	40.04 (0.00)
Random-effects Lagrange multiplier test	403.16 (0.000)	43.06 (0.00)	73.90 (0.00)	5.85 (0.00)	129.41 (0.00)
Hausman test prob.	0.16	0.838	0.128	0.48	0.18
Breusch–Pagan LM test	2985.655 (0.00)	2883.391 (0.00)	2638.482 (0.00)	2862.560 (0.00)	2868.142 (0.00)
Pesaran scaled LM test	24.59 (0.00)	22.78657 (0.00)	18.45 (0.00)	22.41 (0.00)	22.51 (0.00)
Pesaran CD test	−0.57 (0.56)	0.248 (0.80)	0.36 (0.71)	1.01 (0.62)	−0.49 (0.62)

Note. ***, **, and * mean statistically significant at 1%, 5%, and 10%; () represents the probability.

opinion [127–129], according to which women show better communal and ethical values through their social roles than men.

7. Conclusion, Limits, and Future Research Avenues

The influence of the size and gender diversity of a company's board and team of executives on financial performance is a common topic much debated in the literature in recent years but still of great interest due to its possibilities that allow improvement among the contradictory results and create new avenues for more in-depth research. This study conducted an empirical cross-sectional and time-series data analysis on BSE listed companies with the purpose to analyze the impact of the size and executives' board gender diversity on the financial performance of companies. Likewise, according to Vintila et al. [66], Achim et al. [23], Borlea et al. [67], Mihail and Micu [64], and Pintea et al. [68] this study focused on the influence of the board of executive directors in the context of a slow but sustained evolution of Romanian corporate governance regulations and practices. The most significant theories (agency theory, resource dependence theory, and upper echelon theory) that underpin the relationship between the composition and diversity of boards and business performance have shown that greater gender diversity among CEOs can influence performance measurement indicators. Based on the theoretical framework provided by upper echelon theory, we introduced and used in this study the disclosure index on CEOs' characteristics to moderate the interaction between gender diversity and financial performance. In this aspect, to our knowledge, our study is unique among similar investigations conducted on Romanian listed companies. Also, assessment to the impact of management gender diversity on financial performance for the years 2011–2019 was chosen not only individual indicators but also the methodology resorted to the construction of a composite indicator based on multiway PCA using panel data. After running ten models using panel EGLS, which involved five indicators of financial performance and two indicators for management gender diversity, we proved that there is a positive impact of the proportion of women in the executive board on financial performance, the former measured through the composite index, ROA, ROE, and SOL. However, in the case of the Blau index, the statistically significant impact of gender diversity on financial performance was found only for global solvability. Possible explanations for this result can be identified in the particularities of the Romanian business environment and in the greater inclination of Romanian companies to evaluate financial performance through liquidity indicators. Future research in this direction is needed to get clearer answers. It is also worth noting that SOL is an indicator with relevant results, which does not lead to errors in interpretations, unlike some return ratios, where a positive value can be obtained from the calculation; however, the indicators included in the calculation record negative values (for instance, the positive value of ROE when the net income and owners' equity are negative). The results of the panel data analysis by the random-effects model showed that a higher management board size can be associated with better company performance measured by the composite index, ROA, ROE, and EPS.

Like any empirical study, this study has its limitations that can be recognized in terms of sampled companies, selection of variables, and the data set, which generates issues related to endogeneity. Thus, further investigation may involve improvements on data, insertion of other control variables, the extension of time, and testing of the moderating effect of nonfinancial variables. Findings of the study lead to practical but regulatory implications, as well. Therefore, looking at the top executives' team composition by gender, the board can discuss and look after an optimal balance between the members of the directors and executive board. As regulatory consequences, we can aspect that other qualitative changes in corporate governance rules or practices may shape the outcomes of further similar empirical endeavors.

Data Availability

The research uses only publicly available data, disclosed in the annual reports of selected companies, as mentioned in Section 3 of the study. Therefore, the data regarding the analyzed financial indicators, the gender composition of executive directors, and the information related to their characteristics, for the period 2011–2019, were collected from the Bucharest Stock Exchange website (https://bvb.ro/) and accessing companies' websites. Further detailed information on the data can be provided upon request (vbogdan@uoradea.ro).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

References

[1] "Eurostat data," 2022, https://ec.europa.eu/eurostat/databrowser/view/sdg_05_60/default/table?lang=en/.

[2] S. Guga and A. Sindrestean, "Gender economic inequalities in Romania, friendrich ebert stiftung," 2022, http://library.fes.de/pdf-files/bueros/bukarest/18613.pdf/.

[3] Government decision no. 365 of 24 may 2018 for the approval of the national strategy on the promotion of equal opportunities and treatment between women and men and the prevention and fight against domestic violence for the period 2018-2021 and the operational plan for the implementation of the national strategy on the promotion of equal opportunities and treatment and men and the prevention and fight against domestic violence for the period 2018-2021.

[4] Law 202/2002 on equal opportunities between women and men, which specifically focused on gender equality (gender equality law).

[5] Romanian Parliament, law 178/2018 on amending and supplementing law 202/2002 on equal opportunities and treatment.

[6] J. Elliott and R. Smith, "Ethnic matching of supervisors to subordinate work groups: findings on bottom-up ascription

and social closure," *Social Problems*, vol. 48, no. 2, pp. 258–276, 2001.

[7] C. C. Eckel and P. J. Grossman, "Sex differences and statistical stereotyping in attitudes toward financial risk," *Evolution and Human Behavior*, vol. 23, no. 4, pp. 281–295, 2002.

[8] C. Francoeur, R. Labelle, and B. Sinclair-Desgagné, "Gender diversity in corporate governance and top management," *Journal of Business Ethics*, vol. 81, no. 1, pp. 83–95, 2008.

[9] P. Sapienza, L. Zingales, and D. Maestripieri, "Gender differences in financial risk aversion and career choices are affected by testosterone," *Proceedings of the National Academy of Sciences*, vol. 106, no. 36, pp. 15268–15273, 2009.

[10] A. Kirsch, "The gender composition of corporate boards: a review and research agenda," *The Leadership Quarterly*, vol. 29, no. 2, pp. 346–364, 2018.

[11] S. Nielsen and M. Huse, "The contribution of women on boards of directors: going beyond the surface," *Corporate Governance: An International Review*, vol. 18, no. 2, pp. 136–148, 2010.

[12] C. Bart and G. McQueen, "Why women make better directors," *International Journal of Business Governance and Ethics*, vol. 8, no. 1, pp. 93–99, 2013.

[13] R. B. Adams and P. Funk, "Beyond the glass ceiling: does gender matter?" *Management Science*, vol. 58, no. 2, pp. 219–235, 2012.

[14] T. Compernolle, "Communication of the external auditor with the audit committee: managing impressions to deal with multiple accountability relationships," *Accounting, Auditing & Accountability Journal*, vol. 31, no. 3, pp. 900–924, 2018.

[15] R. B. Adams, J. de Haan, S. Terjesen, and H. van Ees, "Board diversity: moving the field forward," *Corporate Governance: An International Review*, vol. 23, no. 2, pp. 77–82, 2015.

[16] A. Amin, R. Ali, R. Rehman, M. A. Naseem, and A. I. Ahmad, *Female Presence in Corporate Governance, Firm Performance, and the Moderating Role of Family Ownership*, Economic Research-Ekonomska Istraživanja, 2021.

[17] M. Adusei, S. Y. Akomea, and K. Poku, "Board and management gender diversity and financial performance of microfinance institutions," *Cogent Business & Management*, vol. 4, 2017.

[18] D. A. Carter, B. J. Simkins, and W. G. Simpson, "Corporate governance, board diversity and firm value," *The Financial Review*, vol. 38, no. 1, pp. 33–53, 2003.

[19] P. Dutta and S. Bose, "Gender diversity in the boardroom and financial performance of commercial banks: evidence from Bangladesh," *Cost and Management*, vol. 34, no. 6, pp. 70–74, 2006.

[20] W. A. Khan and J. P. Vieito, "Ceo gender and firm performance," *Journal of Economics and Business*, vol. 67, pp. 55–66, 2013.

[21] A. Cook and C. Glass, "Diversity begets diversity? The effects of board composition on the appointment and success of women CEOs," *Social Science Research*, vol. 53, pp. 137–147, 2015.

[22] S. Terjesen and V. Singh, "Female presence on corporate boards: a multi-country study of environmental context," *Journal of Business Ethics*, vol. 83, no. 1, pp. 55–63, 2008.

[23] M. V. Achim, S. N. Borlea, and C. Mare, "Corporate governance and business performance: evidence for the Romanian economy," *Journal of Business Economics and Management*, vol. 17, no. 3, pp. 458–474, 2016.

[24] N. Reguera-Alvarado, P. Fuentes, and J. Laffarga, "Does board gender diversity influence financial performance? Evidence from Spain," *Journal of Business Ethics*, vol. 141, no. 2, pp. 337–350, 2017.

[25] J. E. Core, W. R. Guay, and T. O. Rusticus, "Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectations," *The Journal of Finance*, vol. 61, no. 2, pp. 655–687, 2006.

[26] A. J. Hillman and T. Dalziel, "Board of directors and firm performance: integrating agency and resource dependence perspectives," *Academy of Management Review*, vol. 28, no. 3, pp. 383–396, 2003.

[27] M. Jensen, "The modern industrial revolution, exit and the failure of internal control systems," *The Journal of Finance*, vol. 48, no. 3, pp. 831–880, 1993.

[28] G. V. Krishnan and L. M. Parsons, "Getting to the bottom line: an exploration of gender and earnings quality," *Journal of Business Ethics*, vol. 78, pp. 65–76, 2008.

[29] R. B. Adams and D. Ferreira, "Women in the boardroom and their impact on governance and performance," *Journal of Financial Economics*, vol. 94, no. 2, pp. 291–309, 2009.

[30] F. A. Gul, B. Srinidhi, and A. C. Ng, "Does board gender diversity improve the informativeness of stock prices?" *Journal of Accounting and Economics*, vol. 51, no. 3, pp. 314–338, 2011.

[31] P. McGuinness, K. Lam, and J. Vieito, "Gender and other major board characteristics in China: explaining corporate dividend policy and governance," *Asia Pacific Journal of Management*, vol. 32, no. 4, pp. 989–1038, 2015.

[32] M. H. Chen, S. J. Chen, H. W. Kot, D. Zhu, and Z. Wu, "Does gender diversity matter to hotel financial performance?" *International Journal of Hospitality Management*, vol. 97, 2021.

[33] Y. Chen, J. D. Eshleman, and J. S. Soileau, "Board gender diversity and internal control weaknesses," *Advances in Accounting*, vol. 33, pp. 11–19, 2016.

[34] J. Galbreath, "Is board gender diversity linked to financial performance? The mediating mechanism of CSR," *Business & Society*, vol. 57, no. 5, pp. 863–889, 2018.

[35] L. Cabeza-García, R. Fernandez-Gago, and M. Nieto, "Do board gender diversity and director typology impact CSR reporting?" *European Management Review*, vol. 15, no. 4, pp. 559–575, 2018.

[36] V. K. Gupta, S. Mortal, B. Chakrabarty, X. Guo, and D. B. Turban, "CFO gender and financial statement irregularities," *Academy of Management Journal*, vol. 63, no. 3, pp. 802–831, 2020.

[37] R. Schubert, M. Brown, M. Gysler, and H. W. Brachinger, "Financial decision-making: are women really more risk-averse?" *The American Economic Review*, vol. 89, no. 2, pp. 381–385, 1999.

[38] A. Habib and M. Hossain, "CEO/CFO characteristics and financial reporting quality: a review," *Research in Accounting Regulation*, vol. 25, no. 1, pp. 88–100, 2013.

[39] B. Francis, I. Hasan, J. C. Park, and Q. Wu, "Gender differences in financial reporting decision making: evidence from accounting conservatism," *Contemporary Accounting Research*, vol. 32, no. 3, pp. 1285–1318, 2015.

[40] J. Pfeffer and G. R. Salancik, *The External Control of Organizations: A Resource Dependence Perspective*, Harper & Row, New York, 1978.

[41] D. A. Carter, F. D'Souza, B. J. Simkins, and W. G. Simpson, "The gender and ethnic diversity of US boards and board committees and firm financial performance," *Corporate Governance: An International Review*, vol. 18, pp. 396–414, 2010.

[42] A. J. Hillman, A. A. Cannella, and R. L. Paetzold, "The resource dependence role of corporate directors: strategic adaption of board composition in response to environmental change," *Journal of Management Studies*, vol. 37, pp. 235–255, 2000.

[43] Y. Liu, Z. Wei, and F. Xie, "Do women directors improve firm performance in China?" *Journal of Corporate Finance*, vol. 28, pp. 169–184, 2014.

[44] H. Aguinis and A. Glavas, "What we know and don't know about corporate social responsibility: a review and research agenda," *Journal of Management*, vol. 38, no. 4, pp. 932–968, 2012.

[45] M. M. Alonso-Almeida, J. Perramon, and L. Bagur, "Women managers and corporate social responsibility (CSR) in Spain: perceptions and drivers," *Women's Studies International Forum*, vol. 50, pp. 47–56, 2015.

[46] A. J. Hillman, A. A. Cannella, and I. C. Harris, "Women and racial minorities in the boardroom: how do directors differ?" *Journal of Management*, vol. 28, no. 6, pp. 747–763, 2002.

[47] J. Gabrielsson and M. Huse, "Context, behaviour, and evolution: challenges in research on boards and governance," *International Studies of Management & Organization*, vol. 34, pp. 11–36, 2004.

[48] C. A. Peterson and J. Philpot, "Women's roles on U. S. Fortune 500 boards: director expertise and committee memberships," *Journal of Business Ethics*, vol. 72, pp. 177–196, 2007.

[49] D. C. Hambrick and P. A. Mason, "Upper echelons: the organization as a reflection of its top managers," *Academy of Management Review*, vol. 9, no. 2, pp. 193–206, 1984.

[50] D. C. Hambrick, "Upper echelons theory: an update," *Academy of Management Review*, vol. 32, no. 2, pp. 334–343, 2007.

[51] J. Xie, W. Nozawa, and S. Managi, "The role of women on boards in corporate environmental strategy and financial performance: a global outlook," *Corporate Social Responsibility and Environmental Management*, vol. 27, no. 5, pp. 2044–2059, 2020.

[52] J. You, S. Terjesen, and D. Bilimoria, *Women in the Upper Echelons: Women on Corporate Boards and in Top Management Teams*, Business and Management-Oxford Research Encyclopedia, 2018.

[53] A. A. Suciu, D. Paun, and F. S. Duma, "Sustainability of financial performance in relation to gender diverse boards: a comparative analysis of French and Romanian listed companies on stock exchanges," *Sustainability*, vol. 13, 2021.

[54] M. A. Carpenter, "The implications of strategy and social context for the relationship between top management team heterogeneity and firm performance," *Strategic Management Journal*, vol. 23, no. 3, pp. 275–284, 2002.

[55] M. A. Carpenter, T. G. Pollock, and M. Leary, "Testing a model of reasoned risk-taking: governance, the experience of principals and agents, and global strategy in high-technology IPO firms," *Strategic Management Journal*, vol. 24, pp. 803–820, 2003.

[56] V. M. Papadakis and P. Barwise, "How much do CEOs and top managers matter in strategic decision-making," *British Journal of Management*, vol. 13, pp. 83–95, 2002.

[57] M. A. Carpenter, M. A. Geletkanycz, and W. G. Sanders, "Upper echelons research revisited: antecedents, elements, and consequences of top management team composition," *Journal of Management*, vol. 30, no. 6, pp. 749–778, 2004.

[58] C. Rose, "Does female board representation influence firm financial performance? The Danish evidence," *Corporate Governance: An International Review*, vol. 15, no. 2, pp. 404–413, 2007.

[59] K. Campbell and A. Mínguez-Vera, "Gender diversity in the boardroom and firm financial performance," *Journal of Business Ethics*, vol. 83, no. 3, pp. 435–451, 2008.

[60] J. Jermias and L. Gani, "The impact of board capital and board characteristics on firm performance," *The British Accountig Review*, vol. 46, no. 2, pp. 135–153, 2014.

[61] C. Post and K. Byron, "Women on boards and firm financial performance: a meta-analysis," *Academy of Management Journal*vol. 58, no. 5, pp. 1546–1571, 2015.

[62] M. C. Pucheta-Martínez and I. Gallego-Álvarez, "Do board characteristics drive firm performance? An international perspective," *Review of Managerial Science*, vol. 14, no. 6, pp. 1251–1297, 2020.

[63] M. A. Naseem, J. Lin, R. U. Rehman, M. I. Ahmad, and R. Ali, "Does capital structure mediate the link between CEO characteristics and firm performance?" *Management Decision*, vol. 58, no. 1, pp. 164–181, 2020.

[64] B. A. Mihail and C. D. Micu, "The influence of the independent non-executive board members on the financial performance of the companies listed in the bucharest stock exchange," *Journal of Risk and Financial Management*, vol. 14, 2021.

[65] G. Vintila and S. C. Gherghina, "Board of directors independence and firm value: empirical evidence based on the Bucharest stock exchange listed companies," *International Journal of Economics and Financial Issues*, vol. 3, no. 4, pp. 885–900, 2013.

[66] G. Vintila, M. Onofrei, and S. C. Gherghina, "The effects of corporate board and CEO characteristics on firm value: empirical evidence from listed companies on the Bucharest stock exchange," *Emerging Markets Finance and Trade*, vol. 51, no. 6, pp. 1244–1260, 2015.

[67] S. N. Borlea, M. V. Achim, and C. Mare, "Board characteristics and firm performances in emerging economies lessons from Romania," *Economic Research-Ekonomska Istraživanja*, vol. 30, no. 1, pp. 55–75, 2017.

[68] M. O. Pintea, A. M. Pop, M. D. Gavriletea, and I. C. Sechel, "Corporate governance and financial performance: evidence from Romania," *Journal of Economics Studies*, vol. 48, no. 8, pp. 1573–1590, 2021.

[69] O. Bogdan and A. Dumitrescu, "The compliance of the Romanian listed companies with the principles and provisions of the corporate governance code," *Journal of Corporate Governance, Insurance, and Risk Management*, vol. 7, no. 2, pp. 55–69, 2020.

[70] N. Feleaga, L. Feleaga, V. D. Dragomir, and A. D. Bigioi, "Corporate governance in emerging economies: the case of Romania," *Theoretical and Applied Economics*, vol. 18, no. 9, pp. 5–16, 2011.

[71] M. Ionascu and L. Olimid, "The impact of corporate governance practices on financial analysts' forecasts: the case of Romania," *Revista de Audit Financiar*, vol. 10, no. 88, pp. 31–36, 2012.

[72] C. Bocean and C. M. Barbu, "Corporate governance and firm performance," *Management and Marketing Journal*, vol. 5, no. 1, pp. 125–131, 2007.

[73] T. Dănescu and M. A. Popa, "Public health and corporate social responsibility: exploratory study on pharmaceutical companies in an emerging market," *Globalization and Health*, vol. 16, 2020.

[74] S. Terjesen, R. V. Aguilera, and R. Lorenz, "Legislating a woman's seat on the board: institutional factors driving

gender quotas for boards of directors," *Journal of Business Ethics*, vol. 128, pp. 233–251, 2014.

[75] M. C. Pucheta-Martínez, "The role of the Board of Directors in the creation of value for the company," *Spanish Accounting Review*, vol. 18, no. 2, pp. 148–161, 2015.

[76] H. Isidro and M. Sobral, "The effects of women on corporate boards on firm value, financial performance, and ethical and social compliance," *Journal of Business Ethics*, vol. 132, no. 1, pp. 1–19, 2014.

[77] M. T. Hasan, M. S. Molla, and F. Khan, "Effect of board and audit committee characteristics on profitability: evidence from pharmaceutical and chemical industries in Bangladesh," *Finance & Economics Review*, vol. 1, no. 1, pp. 64–76, 2019.

[78] W. Yang, J. Yang, and Z. Gao, "Do female board directors promote corporate social responsibility? An empirical study based on the critical mass theory," *Emerging Markets Finance and Trade*, vol. 55, no. 15, pp. 3452–3471, 2019.

[79] M. Chijoke-Mgbame, A. Boateng, and C. O. Mgbame, "Board gender diversity, audit committee and financial performance: evidence from Nigeria," *Accounting Forum*, vol. 44, no. 2, pp. 262–286, 2020.

[80] T. Nguyen, S. Locke, and K. Reddy, "Does boardroom gender diversity matter? Evidence from a transitional economy," *International Review of Economics & Finance*, vol. 37, pp. 184–202, 2015.

[81] C. Wiley and M. Monllor-Tormos, "Board gender diversity in the STEM&F sectors: the critical mass required to drive firm performance," *Journal of Leadership & Organizational Studies*, vol. 25, no. 3, pp. 290–308, 2018.

[82] H. J. Song, Y. N. Yoon, and K. H. Kang, "The relationship between board diversity and firm performance in the lodging industry: the moderating role of internationalization," *International Journal of Hospitality Management*, vol. 86, 2020.

[83] N. L. Erhardt, J. D. Werbel, and C. B. Shrader, "Board of director diversity and firm financial performance," *Corporate Governance: An International Review*, vol. 11, no. 2, pp. 102–111, 2003.

[84] F. Arenas-Torres, M. Bustamante-Ubilla, and R. Campos-Troncoso, "Diversity of the board of directors and financial performance of the firms," *Sustainability*, vol. 13, no. 21, 2021.

[85] L. Chapple and J. Humphrey, "Does board gender diversity have a financial impact? Evidence using stock portfolio performance," *Journal of Business Ethics*, vol. 122, no. 4, pp. 709–723, 2014.

[86] S. Reddy and A. M. Jadhav, "Gender diversity in boardrooms-a literature review," *Cogent Economics & Finance*, vol. 7, 2019.

[87] I. Gallego-Álvarez, I. M. García-Sánchez, and L. Rodríguez-Dominguez, "The influence of gender diversity on corporate performance," *Revista de contabilidad*, vol. 13, no. 1, pp. 53–88, 2010.

[88] R. Hassan and M. Marimuthu, "Contextualizing comprehensive board diversity and firm financial performance: integrating market, management and shareholder's perspective," *Journal of Management and Organization*, vol. 24, no. 5, pp. 634–678, 2018.

[89] F. Arenas-Torres, M. Bustamante-Ubilla, and R. Campos-Troncoso, "The incidence of social responsibility in the adoption of business practices," *Sustainability*, vol. 13, no. 5, 2021.

[90] S. Abdullah, K. N. Ismail, and L. Nachum, "Does having women on boards create value? The impact of societal perceptions and corporate governance in emerging markets," *Strategic Management Journal*, vol. 37, pp. 466–476, 2016.

[91] D. Palmer and B. M. Barber, "Challengers, elites, and owning families: a social class theory of corporate acquisitions in the 1960s," *Administrative Science Quarterly*, vol. 46, no. 1, pp. 87–120, 2001.

[92] O. N. Bordean and A. Borza, "Boards' attributes and company performance: the Romanian experience," *Economics and Sociology*, vol. 10, no. 2, pp. 61–73, 2017.

[93] D. R. Dalton, C. M. Daily, A. E. Ellstrand, and J. L. Johnson, "Meta-analytic reviews of board composition, leadership structure, and financial performance," *Strategic Management Journal*, vol. 19, no. 3, pp. 269–290, 1998.

[94] P. M. Guest, "The determinants of board size and composition: evidence from the UK," *Journal of Corporate Finance*, vol. 14, no. 1, pp. 51–72, 2008.

[95] R. Aggarwal, I. Erel, R. Stulz, and R. Williamson, "Differences in governance practices between U.S. and foreign firms: measurement, causes, and consequences," *Review of Financial Studies*, vol. 22, no. 8, pp. 3131–3169, 2009.

[96] R. B. Adams and D. Ferreira, "A theory of friendly boards," *The Journal of Finance*, vol. 62, pp. 217–250, 2007.

[97] C. G. Raheja, "Determinants of board size and composition: a theory of corporate boards," *Journal of Financial and Quantitative Analysis*, vol. 40, no. 2, pp. 283–306, 2005.

[98] R. La Porta, F. Lopez-de-Silanes, and A. Shleifer, "The economic consequences of legal origins," *Journal of Economic Literature*, vol. 46, no. 2, pp. 285–332, 2008.

[99] N. DiTomaso, C. Post, and R. Parks-Yancy, "Workforce diversity and inequality: power, status, and numbers," *Annual Review of Sociology*, vol. 33, pp. 473–501, 2007.

[100] M. Torchia, A. Calabro, and M. Huse, "Women directors on corporate boards: from tokenism to critical mass," *Journal of Business Ethics*, vol. 102, no. 2, pp. 299–317, 2011.

[101] N. Gordini and E. Rancati, "Gender diversity in the Italian boardroom and firm financial performance," *Management Research Review*, vol. 40, no. 1, pp. 75–94, 2017.

[102] R. C. Anderson, D. M. Reeb, A. Upadhyay, and W. Zhao, "The economics of director heterogeneity," *Financial Management*, vol. 40, no. 1, pp. 5–38, 2011.

[103] M. Rossi, S. Galasso, and A. Capasso, "Women do it better: an investigation on the association between gender diversity in board of directors and the financial performance," *International Journal of Economics and Financial Issues*, vol. 7, no. 6, pp. 41–50, 2017.

[104] K. Kompa and D. Witkowska, "Relations between changes of women share in management and ROE of public Companies," *Quantitative Methods in Economic Research*, vol. 18, no. 4, pp. 614–623, 2017.

[105] C. P. Green and S. Homroy, "Female directors, board committees and firm performance," *European Economic Review*, vol. 102, no. 2, pp. 19–38, 2018.

[106] G. G. Noja, E. Thalassinos, M. Cristea, and I. M. Grecu, "The interplay between board characteristics, financial performance, and risk management disclosure in the financial services sector: new empirical evidence from Europe," *Journal of Risk and Financial Management*, vol. 14, 2021.

[107] M. Bennouri, T. Chtioui, H. Nagati, and M. Nekhili, "Female board directorship and firm performance: what really matters?" *Journal of Banking & Finance*, vol. 88, pp. 267–291, 2018.

[108] S. Brahma, C. Nwafor, and A. Boateng, "Board gender diversity and firm performance: the UK evidence,"

International Journal of Finance & Economics, vol. 26, no. 4, pp. 5704–5719, 2021.

[109] M. Orlitzky, F. L. Schmidt, and S. L. Rynes, "Corporate social and financial performance: a meta-analysis," *Organization Studies*, vol. 24, no. 3, pp. 403–441, 2003.

[110] J. D. Margolis, H. A. Elfenbein, and J. P. Walsh, "Does it pay to Be good? A meta-analysis and redirection of research on the relationship between corporate social and financial performance," *Ann Arbor*, vol. 1001, pp. 48109–51234, 2007.

[111] H. Wang, J. Choi, and J. Li, "Too little or too much? Untangling the relationship between corporate philanthropy and firm financial performance," *Organization Science*, vol. 19, no. 1, pp. 143–159, 2008.

[112] A. Arora, "Gender diversity in boardroom and its impact on firm performance," *Journal of Management & Governance*, vol. 12, 2021.

[113] C. Wang, X. Deng, S. Álvarez-Otero et al., "Impact of women and independent directors on corporate social responsibility and financial performance: empirical evidence from an emerging economy," *Sustainability*, vol. 13, 2021.

[114] M. S. Molla, M. T. Hasan, M. H. Miraz, M. T. Azim, and Md. K. Hossain, "The influence of directors' diversity and corporate sustainability practices on firm performance: evidence from Malaysia," *Journal of Asian Finance, Economics and Business*, vol. 8, no. 6, pp. 201–212, 2021.

[115] T. Miller and M. C. Triana, "Demographic diversity in the boardroom: mediators of the board diversity–firm performance relationship," *Journal of Management Studies*, vol. 46, no. 5, pp. 755–786, 2009.

[116] D. A. Harrison and K. J. Klein, "What's the difference? Diversity constructs as separation, variety, or disparity in organizations," *Academy of Management Review*, vol. 32, no. 4, pp. 1199–1228, 2007.

[117] P. M. Blau, *Inequality and Heterogeneity: A Primitive Theory of Social Structure*, Free Press, New York, NY, USA, 1977.

[118] L. Jiang, J. Cherian, M. S. Sial et al., "The moderating role of CSR in board gender diversity and firm financial performance: empirical evidence from an emerging economy," *Economic Research-Ekonomska Istraživanja*, vol. 34, no. 1, pp. 2354–2373, 2020.

[119] J. Pallant, *SPSS Survival Manual*, Open University Press, Maidenhead, UK, 2007.

[120] C. Brooks, *Introductory Econometrics for Finance*, Cambridge University Press, Cambridge, UK, 2 edition, 2014.

[121] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, Pearson Higher Education, Upper Saddle River, NJ, USA, Global edition, 2010.

[122] T. S. Breusch and A. R. Pagan, "A simple test for heteroscedasticity and random coefficient variation," *Econometrica*, vol. 47, no. 5, pp. 1287–1294, 1979.

[123] R. De Hoyos and V. Sarafidis, "Testing for cross-sectional dependence in panel-data models," *STATA Journal*, vol. 6, no. 4, pp. 482–496, 2006.

[124] D. Bailey and J. N. Katz, "Implementing panel corrected standard errors in R: the PCSE package," *Journal of Statistical Software*, vol. 42, no. c01, 2011.

[125] J. Chen, W. S. Leung, and M. Goergen, "The impact of board gender composition on dividend payouts," *Journal of Corporate Finance*, vol. 43, pp. 86–105, 2017.

[126] M. Kılıç and C. Kuzey, "The effect of board gender diversity on firm performance: evidence from Turkey," *Gender in Management*, vol. 31, no. 7, pp. 434–455, 2016.

[127] P. P. Gupta, K. C. Lam, H. Sami, and H. Zhou, "Board diversity and its long-term effect on firm financial and non-financial performance," 2015, https://ssrn.com/abstract=2531212.

[128] S. K. Huang, "The impact of CEO characteristics on corporate sustainable development," *Corporate Social Responsibility and Environmental Management*, vol. 20, no. 4, pp. 234–244, 2013.

[129] H. Jo and M. A. Harjoto, "Corporate governance and firm value: the impact of corporate social responsibility," *Journal of Business Ethics*, vol. 103, no. 3, pp. 351–383, 2011.

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Research Article

Study on Effect of Consumer Information in Personal Credit Risk Evaluation

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This study selects Chinese borrowers' information from a platform that has both online shopping and consumer loan service as sample, studies the effect of consumer information in personal credit risk evaluation, and uses the lLogistic regression model, light gradient boosting machine (LightGBM) algorithm, and Shapley Additive Explanation (SHAP). The results show that the information of all consumer loan groups cannot be covered by traditional credit information. Consumer information can help predict the behavior of borrower's repayment and provide support for personal credit risk evaluation effective. Adding consumption information to the personal credit risk evaluation model can improve the accuracy of the model effectively. The model variables are ranked by feature importance, and there are 5 consumption indicators in the first 5 indicators of feature importance, which further verifies the value and effect of consumption information in personal credit risk evaluation. This study not only reveals the effect and value of consumer information in personal credit risk evaluation effectively, but also provides new ideas for the development of consumer financial market.

1. Introduction

At present, a new round of global scientific and technological revolution continues to deepen, financial technology is rising rapidly, and new business forms, new models, and new products emerge one after another. It not only changes the operation mode of traditional financial services, but also promotes the development of Internet personal consumption loans. At the same time, the vigorous development of personal consumer loans will have an impact on customers' intertemporal consumption behavior. Under this background, the personal credit risk evaluation index system is becoming more and more abundant, and multi-dimensional and massive data are fused and processed. Big data credit investigation is an inevitable trend of personal credit risk evaluation. Nevertheless, some data are missing and the amount of data is lacking, so it is difficult to train [1]. The PBC credit investigation system cannot cover all borrowers' information, which requires financial institutions to explore indicators beyond traditional personal credit risk evaluation index system. The traditional evaluation index system rarely uses consumption information as the evaluation index of personal credit risk. Can consumer information be used for personal credit risk assessment? What is the value and function of consumer information in personal credit risk evaluation? This is the question to be answered in this paper. This study uses the Chinese borrower's data of a platform that has both online shopping and consumer loan to explore this problem.

Driven by financial technology, Internet consumer loans came into being and have made great progress. In early 2014, JD finance launched the "JD white note" to open the chapter of Internet consumer credit. Ant group followed closely with the launch of "Ant Huabei." Since 2015, commercial banks, consumer finance companies, and other financial institutions have vigorously deployed Internet consumer finance business. Up to now, the scale of Internet consumer credit has expanded rapidly, with a scale of 18.7 billion RMB at the beginning of 2014 and 15.4 trillion RMB at the end of 2020, with a compound annual growth rate of 206%. By the end of

2020, there were 778 million credit cards and debit-credit cards used in China, and the number of cards per capita was 0.56. According to the questionnaire analysis of 110 cities in 30 provinces and cities in China by China Institute of Economic Thought and Practice of Tsinghua University, residents' acceptance and satisfaction with consumer finance companies are increasing, and the annual growth rate of adults willing to accept consumer finance services is more than 10%. Compared with the blowout-type development of Internet loan market, the improvement of personal credit risk management ability is insufficient slightly. The most important factor restricting the in-depth study of consumer finance is the lack of micro-data and continuous micro-household sampling [2]. The use of utilizing new information beyond traditional credit investigation methods by financial science and technology innovation helps to reduce information asymmetry in the consumer credit market. It provides an important channel for marginal groups of traditional financial services to obtain high-quality credit services and establish personal credit records [3].

Personal consumer loans have the characteristics of "small amount, unsecured and flexible," and the default risk cannot be quantitatively monitored through the traditional postloan behavior score. Therefore, preloan review has become an important measure to prevent credit risk. In recent years, the asset quality of personal consumer loans has been moving downward, and the nonperforming rate has continued to grow, which has brought new requirements and challenges to the credit risk management of consumer loans. At present, the personal credit-related information comes from the personal credit information of the People's Bank of China. The mainstream three-party credit service institutions such as Baihang credit and Bairong Inc. also provide effective data for personal credit risk evaluation. However, the personal credit reporting system of the people's Bank of China does not cover enough dimensions in terms of data comprehensiveness, hierarchy, and timeliness. The personal credit information mastered by the third-party data company is different from the traditional credit information, mainly from the customer's loan information and fraud score on P2P network lending platforms, microfinance companies, and other platforms. The introduction of third-party data has confirmed that it has great practical significance to apply information other than the credit investigation information of the People's Bank of China to the credit risk evaluation of personal consumer loans. Different from third-party data, consumer information is highly available, but it cannot reflect the solvency and willingness to repay. Therefore, the value and effect of consumer information in personal credit risk evaluation are worthy of in-depth discussion.

Different from the existing research, this paper has made some progress in the following two aspects: first of all, this paper deeply analyzes the differences between consumer information and traditional credit information in personal credit risk evaluation. Second, it proves that consumer information can be an effective supplement to traditional credit information in the practice of personal credit risk evaluation.

2. Previous Research

For a long time, information asymmetry is the main factor affecting personal credit risk. Stiglitz and Weiss [4] first proposed that although the borrower's credit history information (such as credit rating and historical performance) is open to all investors, network anonymity may aggravate the typical information asymmetry of online lending [4]. Information asymmetry also exists in the online lending market [5, 6]. The existence of information asymmetry will lead to two kinds of effects of market shrinkage: one is the "loan sparing"—the effective supply of the market is shrinking; the second is the "crowding out"—the effective demand of the market is shrinking [7].

In the research on the influencing factors of personal loan default, scholars found that there are internal and external factors, which can also be reflected in "hard information" and "soft information" [8, 9]. "Hard information" refers to personal information with strong authenticity and objective existence, such as age, gender, job grade, and credit score, and "soft information" refers to the borrower's group, the number of friends in the social network, consumption ability level, macro-information, and other information [10, 11]. Su and Cheng [12] found that "soft information" is also valuable in their research on the factors affecting the default behavior of online lending borrowers [12]. Chi et al. [13] showed that macroeconomic factors have a certain impact on the borrower's repayment [13].

For a long time, establishing an effective personal credit evaluation system is the core content of personal credit risk management. Scholars' research on personal credit risk evaluation mainly includes two aspects: one is the construction of personal credit risk evaluation index system, and the other is the methods of personal credit risk evaluation. Most of the existing evaluation index systems take the indicators in customers' historical credit transactions as the main indicators [14–16]. In the early stage, the credit risk evaluation methods mainly used logistic regression and expert discrimination, and the logistic regression model in the regression analysis model is the most widely used personal credit risk evaluation model so far [17–25]. The core model of FICO score is logistic regression algorithm. At present, China's commercial banks mainly use analytic hierarchy process and fuzzy evaluation method to evaluate the credit risk of borrowing customers [26]. With the development of financial technology and artificial intelligence, machine learning algorithm can predict the default risk of credit subjects more efficiently and accurately. Verleysen and Francois [27] first applied the decision tree method in personal credit evaluation and achieved good evaluation results [27]. Houle et al. [28] improved the decision tree method based on boosting algorithm on the basis of considering the sample attributes of personal credit risk assessment [28].

However, the mainstream credit evaluation mostly uses the borrower's historical loan information to build the evaluation model, which cannot cover all customer groups. This leads to some customers being shut out of mainstream

credit services, unable to obtain financial support and subject to serious financial constraints. In order to break this constraint, it is particularly important to explore whether indicators beyond traditional credit evaluation system can identify credit risk and be used in credit risk evaluation. Bertrand and Kamenica [29] document that owning an IOS device is one of the best predictors for being in the top quartile of the income distribution [29]. Belenzon et al. [30], and Guzman and Stern [31] have documented that customers having their names in the e-mail address are 30% less likely to default [30, 31]. Digital footprints can facilitate access to credit when credit bureau scores do not exist, thereby fostering financial inclusion and lowering inequality [32–36].

It can be seen that information beyond mainstream credit evaluation indicators can also achieve significant results in credit risk evaluation. Continuously mining information beyond mainstream credit evaluation indicators becomes more and more important to reduce the credit risk caused by information asymmetry and can also continuously improve the ability of risk identification [1, 3]. This study focuses on the effect of consumer information in personal credit risk evaluation. Consumer information has the characteristics of high frequency and timeliness, which is different from the traditional credit indicators. This study attempts to use empirical analysis to reveal the effect of consumption information in personal credit risk evaluation.

3. Data and Variable Description

3.1. Sample Selection. The data of this paper come from a commercial bank. Platforms like ANT and JD have certain channels to obtain customers, but they do not have enough funds, while commercial banks have lacked large-scale channels to obtain customers but have funds. Therefore, the joint loan between the platform and the bank came into being in China. We obtained the borrowers' information data from a Chinese platform which cooperated in joint loan from a commercial bank. As a large life service platform, the platform involves food, hotel, tourism, film, and group purchase. As of December 31, 2020, the number of active merchants and annual transaction users of the platform had increased to 6.8 million people and 510 million RMB, respectively. Therefore, it is very persuasive to select the borrowers' information data of the platform as a sample for empirical research. This study constructs an evaluation index system by obtaining the borrowers' behavior of repayment, consumption information of the platform, transaction information of the platform, information of credit card use, credit information of credit card, personal information, and loan information. According to the borrowers' repayment performance on the platform, the customer is defined as "good" or "bad" to explore the effect of consumption information in personal credit evaluation. We selected 185600 customer information data of the credit granted from April 2020 to August 2020, and 50000 pieces of customer information were randomly selected as samples for analysis.

3.2. Variable Description. The core variables involved in the empirical design of this study are as follows.

3.2.1. Behavior of Repayment. Through the vintage analysis of the behavior of repayment of customers on the platform, the results show that when the borrower has overdue for more than 30 days, there is a 93.75% probability that it will continue to be overdue. Therefore, if the overdue days of the borrower are more than 30 days, the customer is defined as "bad customer" (default = 1). On the contrary, if the customer has no overdue performance or the overdue days are not more than 30 days, it is defined as "good customer" (default = 0).

3.2.2. Consumption Information of the Platform. The consumption information of the platform comes from the consumption records of the borrower on the platform. The following three indicators are formed for the processing of the borrower's consumption records on the platform within one year: consumption ability, consumption frequency, and consumption scene.

3.2.3. Transaction Information of the Platform. The transaction information of the platform comes from the borrower's transaction records on the platform within 90 days, including days of transaction, amount of successful transaction, number of successful transaction, and active days.

3.2.4. Information of Credit Card Use. The information of credit card use comes from the borrower's personal credit information, including average quota utilization and maximum quota utilization.

3.2.5. Credit Information of Credit Card. The credit information of credit card also comes from the borrower's personal credit information, including average quota, number, and total amount.

3.2.6. Control Variable. There are two types of control variables: borrower's personal information and loan information. Personal information includes age, gender, and state of marriage and job; loan information includes amount and rate.

The definitions of main variables and descriptive statistics are shown in Tables 1 and 2 respectively.

4. Evaluation Model and Empirical Results

4.1. Construction of Model

4.1.1. The Effect of Consumer Information in Personal Credit Risk Evaluation. In order to explore the effect of consumer information in personal credit risk evaluation deeply, we use logistic regression model for empirical analysis. The dependent variable is customer behavior of repayment. Independent variables include platform consumption

Table 1: Definition of main variables.

Variable type	Variable name	Variable description
Behavior of repayment	Default	If the customer is overdue for more than 30 days, assign 1, and conversely, assign 0
Consumption information of the platform	Consumption ability	Consumption capacity level within one year, consumption amount <30 RMB, assign 1; 30 ≤ consumption amount < 70 RMB, assign 2; 70 ≤ consumption amount < 90 RMB, assign 3; consumption amount ≥90 RMB, assign 4; no consumption record, assign 0
	Consumption frequency	Consumption frequency grade within one year, consumption frequency <3, assign 1; 3 ≤ consumption frequency < 6, assign 2; 6 ≤ consumption frequency < 10, assign 3; consumption frequency ≥10, assign 4; no consumption record, assign 0
	Consumption scene	Number of consumption scenarios within a year, *consumption scene* <2, assign 1; 2 ≤ *consumption scene* < 4, assign 2; *consumption scene* ≥4, assign 3; no consumption record, assign 0
Transaction information of the platform	Days of transaction	Days of transaction ≤1, assign 1; 1 ≤ days of transaction < 4, assign 2; days of transaction ≥4, assign 3; no found, assign 0
	Amount of successful transaction	Amount of successful transaction ≤25, assign 1; 25 ≤ amount of successful transaction < 200, assign 2; amount of successful transaction ≥200, assign 3; no found, assign 0
	Number of successful transaction	Number of successful transactions ≤1, assign 1; 1 ≤ number of successful transactions < 4, assign 2; number of successful transactions ≥4, assign 3; no found, assign 0
	Active days	Active days ≤4, assign 1; 4 ≤ active days < 19, assign 2; active days ≥19, assign 3; no found, assign 0
Information of credit card use	Average quota utilization	Average quota utilization ≤0.35, assign 1; 0.35 ≤ average quota utilization < 0.75, assign 2; 0.75 ≤ average quota utilization < 0.85, assign 3; average quota utilization ≥0.85, assign 4; no found, assign 0
	Maximum quota utilization	Maximum quota utilization ≤0.1, assign 1; 0.1 ≤ maximum quota utilization < 0.3, assign 2; 0.3 ≤ maximum quota utilization < 0.5, assign 3; maximum quota utilization ≥ 0.5, assign 4; no found, assign 0
Credit information of credit card	Average quota	Average quota ≤10000 RMB, assign 1; 10000 ≤ average quota < 30000 RMB, assign 2; 30000 ≤ average quota < 50000 RMB, assign 3; 50000 ≤ average quota < 100000 RMB, assign 4; average quota≥100000 RMB, assign 5; no found, assign 0
	Number	number = 0, assign 1; 1≤number< 3, assign 2; 3≤number <7; 7≤number <12, assign 4; number ≥12, assign 5; no found, assign 0
	Total amount	Total amount ≤10000 RMB, assign 1; 10000 ≤ total amount < 30000 RMB, assign 2; 30000 ≤ total amount < 50000 RMB, assign 3; 50000 ≤ total amount < 100000 RMB, assign 4; total amount ≥100000 RMB, assign 5; no found, assign 0
Personal information	Age	Under 22 years old, assign 1; 22–40 years old, assign 2; beyond 40 years old, assign 3
	Gender	Male, assign 0; female, assign 1
	State of marriage	Unmarried, assign 1; married, assign 2; divorced and other, assign 3; no found, assign 0
	Job	Agriculture, forestry, animal husbandry, and fishery, assign 1; manufacturing, assign 2; social services, assign 3; public service, assign 4; real estate, assign 5; wholesale, assign 6; financial, assign 7; other, assign 8; unknown, assign 9; no found, assign 0
Loan information	Amount	Below 5000 RMB, assign 1; 5000–10000 RMB, assign 2; 10000–20000 RMB, assign 3; 20000–30000 RMB, assign 4; 30000–40000 RMB, assign 5; above 40000 RMB, assign 6
	Rate	Interest rate

Table 2: Descriptive statistics.

Variable	Mean	Min	Max	Standard deviation	Observed value
Default	0.04328	0	1	7275.8	50000
Consumption ability	0.196896	0	4	0.17342	50000
Consumption frequency	1.75604	0	4	0.496516	50000
Consumption scene	1.82742	0	4	0.452636	50000
Days of transaction	2.51908	0	3	0.8303	50000
Amount of successful transaction	2.58016	0	3	0.7904	50000
Number of successful transaction	2.54074	0	3	0.82542	50000
Active days	2.41376	0	3	0.87513	50000
Average quota utilization	1.46706	0	4	0.77997	50000
Maximum quota utilization	2.28846	0	4	1.40822	50000
Average quota	1.57802	0	5	0.7446	50000
Number	2.33848	0	4	1.136	50000
Total amount	2.51658	0	5	1.60343	50000
Age	1.95218	1	3	0.404592	50000
Gender	0.43438	0	1	0.46568	50000
State of marriage	1.61786	0	3	0.6959	50000
Job	7.30406	0	9	2.67282	50000
Amount	2.94646	1	6	2.29651	50000
Rate	16.611588	10.8	23.4	3.23299	50000

information, platform trading information, and credit card usage information; credit card credit information and control variables include the borrower's personal information and loan information.

In order to study the recognition ability and effect of consumer information in personal credit risk evaluation, we constructed five logistic regression models. Model 1 discusses the relationship between traditional credit information and borrower's credit risk. The independent variables include credit card credit information and control variables. Model 2 discusses the relationship between credit card use information and borrower's credit risk. The independent variables include credit card use information and control variables. Model 3 discusses the relationship between platform consumption and transaction information and borrower's credit risk. The independent variables include platform consumption information, platform transaction information, and control variables. Model 4 discusses the relationship between all consumption information obtained in this study and the borrower's credit risk. The independent variables include platform consumption and transaction information, credit card use information, and control variables. Model 5 includes all independent variables. The formula is expressed as follows:

$$\begin{aligned}
\text{Logistic}(\text{default}_i) &= \alpha_1 \text{cc_credit}_i + \alpha_2 \text{control}_i + \varepsilon,\\
\text{Logistic}(\text{default}_i) &= \alpha_1 \text{cc_use}_i + \alpha_2 \text{control}_i + \varepsilon,\\
\text{Logistic}(\text{default}_i) &= \alpha_1 \text{consumption}_i + \alpha_2 \text{trading}_i + \alpha_3 \text{control}_i + \varepsilon,\\
\text{Logistic}(\text{default}_i) &= \alpha_1 \text{consumption}_i + \alpha_2 \text{trading}_i + \alpha_3 \text{cc_use}_i + \alpha_4 \text{control}_i + \varepsilon,\\
\text{Logistic}(\text{default}_i) &= \alpha_1 \text{consumption}_i + \alpha_2 \text{trading}_i + \alpha_3 \text{cc_use}_i + \alpha_4 \text{cc_credit}_i + \alpha_5 \text{control}_i + \varepsilon.
\end{aligned} \tag{1}$$

Among them, default_i is the dependent variable, α is the coefficient, consumption_i, trading_i, cc_use_i, *and* cc_credit_i are the explanatory variable, and ε is a random error term. The logistic regression model was implemented by *s* as 14.3.

4.1.2. Model for Personal Credit Risk Prediction. LightGBM is an open-source, fast, and efficient lifting framework based on a decision tree algorithm, which supports efficient parallel training and can greatly shorten the training time. LightGBM algorithm is a kind of boosting algorithm. Boosting algorithm learns multiple classifiers by changing the weight of training samples and improving the performance of classifiers through linear combination. Boosting formula can be expressed as follows:

$$f(x) = W_O + \sum_{M=1}^{M} Wm\phi m(X). \tag{2}$$

The objective function is

$$\text{Obj}(\theta) = L(\theta) + \Omega(\theta). \tag{3}$$

Among them, $L(\theta)$ is the error function and $\Omega(\theta)$ is the regular term.

LightGBM also seeks the optimal solution by combining the error function with the regular term by constructing the objective function. The objective function is

$$L(j) = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k). \tag{4}$$

The complexity term of the tree in $\Omega(f_k) = \gamma T + 1/2\lambda\|W\|^2$ algorithm includes the regular term of the total number of leaf nodes and the score of leaf nodes, which can produce the phenomenon of skin overfitting. The regular term is

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|W\|^2. \tag{5}$$

LightGBM performs quadratic Taylor expansion on the cost function. Unlike GBDT, LightGBM can not only define the cost function, but also obtain the derivatives of the first and second orders at the same time. Then, the loss function of t is

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f(x_i)_t\right) + \Omega(f_t). \tag{6}$$

The second-order Taylor expansion of (6) is carried out to obtain (7), and the first derivative and second derivative are (8) and (9), respectively:

$$L^{(t)} \approx \sum_{i=1}^{n} l\left(y_i, y_i^{(t-1)} + g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right) + \Omega(f_t), \tag{7}$$

$$g_i = \delta_{\hat{y}^{(t-1)}} L\left(y_i, \hat{y}_i^{(t-1)}\right), \tag{8}$$

$$h_i = \delta^2_{\hat{y}^{(t-1)}} L\left(y_i, \hat{y}_i^{(t-1)}\right). \tag{9}$$

LightGBM divides the eigenvalues into buckets and then constructs the histogram for splitting. The calculation formula is as follows:

$$\text{gain} = \max\left(\text{gain}, \frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{G}{H + \lambda}\right). \tag{10}$$

The samples processed by bucket division not only improve the training speed, but also reduce the complexity of calculation and the occupation of computer memory. Due to the advantages of LightGBM algorithm, it is widely used in many fields. We use LightGBM algorithm to predict personal credit risk.

4.2. Empirical Analysis. By analyzing the real performance of the Chinese borrower's credit risk of a platform integrating both online shopping and consumer loan, we measure the traditional credit information with the borrower's credit card credit information, measure the consumption information with the borrower's consumption information, transaction information, and credit card use information on the platform, and further explore the effect of consumer information in personal credit risk evaluation.

4.2.1. The Effect of Consumer Information on the Borrower's Credit Risk. The results of logistic regression are shown in Table 3. Model 1 discusses the relationship between traditional credit information and borrower's credit risk. The regression coefficient of the average quota is −0.13, which is significant at the 5% significant level. It indicates that the larger the average quota of the borrower, the smaller the credit risk. The regression coefficients of the amount of credit cards and total amount of credit cards are 0.08 and 0.11, respectively, which are significant at the significant level of 5% and 1%, respectively. It indicates that the more credit cards, the greater the total amount of credit card and the greater the credit risk. Model 2 discusses the relationship between credit card use information and borrower's credit risk. The regression coefficient of average quota utilization is 0.22, which is significant at the 1% significant level. It shows that the greater the average quota utilization, the greater the credit risk. The maximum quota utilization of credit card has no significant impact on credit risk. Model 3 discusses the relationship between consumption information of the platform, transaction information of the platform, and borrower's credit risk. Consumption ability, days of transaction, amount of successful transaction, and number of successful transaction have no significant impact on credit risk. The regression coefficients of platform consumption frequency, consumption scene, and active days are −0.14, −0.20, and −0.20, respectively, which are significant at the 1% significant level. It shows that the larger the three variables, the smaller the credit risk. Model 4 explores the relationship between all consumption information obtained and the borrower's credit risk, and the empirical results are consistent with the above analysis. Model 5 discusses the relationship between all independent variables and the borrower's credit risk. State of marriage and rate are positively correlated with the borrower's credit risk at a significant level of 1%. Gender is negatively correlated with the borrower's credit risk at a significant level of 1%-free network, and the peak of the associated credit risk appears between $t = 5 - 10$, which reduces the transmission speed of the associated credit risk. It can be seen that the existence of exposed subjects has a significant delaying effect on the arrival of the peak of the related credit risk infection. When the coefficient of latent transformation $\alpha = 0.2$ and $\alpha = 0.5$, the contagion scale of the related credit risk is less than 0.6. The smaller the coefficient of latent transformation is, the smaller the contagion scale is. It can be seen that the existence of latent subjects has a significant inhibitory effect on the contagion scale of the related credit risk. The smaller the coefficient of latent transformation, the stronger the inhibition. In conclusion, when there are exposed subjects in the network, the latent transformation coefficient has a significant delaying and inhibiting effect on the peak period and the scale of infection of the risk of the associated credit.

4.2.2. Robust Test. In the above empirical analysis, customers overdue for more than 30 days are selected as the definition condition of "bad" customers. In order to verify whether the above empirical analysis results depend on the definition conditions of dependent variables, a robust test will be carried out. Taking "overdue days more than 5 days"

Table 3: Results of logistic regression.

Dependent variable	(1)	(2)	(3)	(4)	(5)
Consumption ability			0.5692 (0.1902)	0.0915 (0.1956)	0.1285 (0.1990)
Consumption frequency			−0.1414*** (0.0575)	−0.1747*** (0.0578)	−0.0376** (0.0658)
Consumption scene			−01989*** (0.0663)	−0.2550*** (0.0667)	−0.1554*** (0.0682)
Days of transaction			0.0619 (0.1138)		0.0498 (0.1152)
Amount of successful transaction			0.0352 (0.0575)		0.0182 (0.0592)
Number of successful transaction			−0.1812 (0.1155)		−0.1371 (0.1170)
Active days			−0.1951*** (0.0341)		−0.1929*** (0.0355)
Average quota utilization		0.2203*** (0.0333)		0.2076*** (0.0333)	0.2004*** (0.0332)
Maximum quota utilization		0.0273 (0.0289)		0.0322 (0.0290)	0.0333 (0.0290)
Average quota	−0.1331** (0.0493)			−0.1262** (0.0493)	−0.1263** (0.0494)
Number	0.0813** (0.0401)			0.0829** (0.0401)	0.0875** (0.0402)
Total amount	0.1137*** (0.0365)			0.1126*** (0.0366)	0.1139*** (0.0367)
Age	0.0897 (0.0586)	0.1030* (0.0580)	0.00083(0.0609)	0.0712 (0.0614)	−0.0757 (0.0614)
Gender	−0.3602*** (0.0476)	−0.3221*** (0.0471)	−0.0360*** (0.0473)	−0.3578*** (0.0480)	−0.3358*** (0.0481)
State of marriage	0.2462*** (0.0369)	0.2028*** (0.0338)	0.0772** (0.0353)	−0.2550*** (0.0387)	0.1029*** (0.0390)
Job	0.0192*** (0.00884)	−0.0221** (0.00837)	−0.0272(0.00831)	−0.00755 (0.00908)	0.00409 (0.00915)
Amount	0.4068* (0.308)	0.3927* (0.2731)	0.4048* (0.2901)	0.3917* (0.2721)	0.3927* (0.2705)
Rate	0.1320*** (0.00733)	0.1320*** (0.00731)	0.1219*** (0.00734)	0.1205*** (0.00737)	0.1218*** (0.00741)
Observations	50000	50000	50000	50000	50000
Pseudo R^2	0.032	0.033	0.033	0.032	0.030

*Note.****,**, and* represent the significance levels of 1%, 5%, and 10%, respectively.

and "overdue days more than 60 days" as dependent variables, empirical tests are carried out for the above models 1, 4, and 5, respectively.

Table 4 shows the logistic regression results of different dependent variables. Consistent with the results of the above main regression, platform consumption information, platform transaction information, and credit card use information are significantly correlated with the borrower's credit risk. Credit card credit information is also significantly related to the borrower's credit risk. Based on the above analysis, the introduction of borrower consumption information on the basis of traditional credit information can better identify credit risk.

4.2.3. The Promotion Effect of Consumption Information on the Model. LightGBM algorithm can predict personal credit risk effectively and rank the importance of indicators. ROC curve can predict the accuracy of the model effectively [37–40]. AUC is the area under the ROC curve, which can explain the prediction accuracy of the model. In order to compare the fitting degree of the two models, we use AUC index to evaluate the model quality [41, 42]. In this study, LightGBM algorithm is used to predict the model results of the above models 1 and 5, respectively, and draw the ROC curve. The AUC index results are shown in Figures 1 and 2. Figure 1 shows the prediction results of model 1 test samples. When there is only traditional credit information, the AUC value is 0.70. Figure 2 shows the prediction results of model 5 test samples, with AUC value of 0.81. It can be seen that the introduction of consumption information on the basis of traditional credit information can improve the accuracy of the model effectively, and the addition of consumption information improves the prediction ability of the model significantly. LightGBM algorithm is implemented by Python 3.7.

Table 4: Results of robust test.

Dependent variable	od5	od5	od5	od60	od60	od60
Consumption ability			0.1929 (0.1854)		0.2792 (0.2025)	0.1387 (0.2124)
Consumption frequency			−0.0335 (0.0600)		−0.1464** (0.0630)	−0.0538 (0.0722)
Consumption scene			−0.1096*** (0.0629)		−0.2543*** (0.0715)	−0.2077*** (0.0736)
Days of transaction			−0.0211 (0.1038)			0.1716 (0.1290)
Amount of successful transaction			0.0204 (0.0540)			0.0164 (0.0647)
Number of successful transaction			0.0204 (0.0540)			0.2911 (0.1305)
Active days			−0.1913*** (0.0324)			−0.1889*** (0.0388)
Average quota utilization		0.1946*** (0.0307)	0.1946*** (0.0307)		0.2030*** (0.0362)	0.1802*** (0.0361)
Maximum quota utilization		0.0526** (0.0262)	0.0526** (0.0262)		0.0311 (0.0318)	0.0385 (0.0319)
Average quota	−0.0827* (0.0449)		−0.0827* (0.0449)		−0.1055** (0.0537)	−0.0983* (0.0538)
Number	0.0876** (0.0368)		0.0876** (0.0368)		0.0952** (0.0439)	0.1013** (0.0441)
Total amount	0.0661** (0.0335)		0.0661** (0.0335)		0.1099*** (0.0400)	0.1099*** (0.0402)
Age	0.0838 (0.0534)	0.00529 (0.0553)	0.0616 (0.0557)	0.1158* (0.0645)	0.0194 (0.0671)	0.0629 (0.0677)
Gender	−0.3545*** (0.0433)	−0.3609*** (0.0430)	−0.3323*** (0.0438)	−0.3558*** (0.0525)	−0.3327*** (0.0521)	−0.3303*** (0.0531)
State of marriage	0.2344*** (0.0337)	0.0922* (0.0321)	−0.1096* (0.0629)	0.2537*** (0.0405)	0.0667* (0.0387)	0.1074** (0.0429)
Job	0.0208*** (0.00806)	−0.0254*** (0.00759)	−0.006*** (0.00831)	−0.0292*** (0.0096)	−0.0405 (0.00902)	−0.0128*** (0.00997)
Amount	0.4027* (0.301)	0.4053* (0.231)	0.4058* (0.2581)	0.3902* (0.2625)	0.3927* (0.2705)	0.4058* (0.2581)
Rate	0.1209*** (0.00665)	0.1109*** (0.00666)	0.1109*** (0.00673)	0.1524*** (0.00812)	0.1430*** (0.00816)	0.1428*** (0.00823)
Observations	50000	50000	50000	50000	50000	50000
Pseudo R2	0.0313	0.0311	0.03105	0.0312	0.0301	0.03109

*Note.****,**, and* represent the significance levels of 1%, 5%, and 10%, respectively.

4.2.4. Feature Importance and SHAP Value of Consumption Information. In order to explore the importance of borrower consumption information and traditional credit information in personal credit risk evaluation, we use LightGBM algorithm and Shapley additive explanation to build a model to rank the feature importance and the impact of consumption information of the platform, transaction information of the platform, and information of credit card. The 12 variables are sorted by importance to generate an importance SHAP value plot, as shown in Figure 3.

According to the ranking results of feature importance and SHAP value, among the top five indicators in the ranking of importance, five consumption information indicators are in 5 places. This also confirms the value and effect of consumer information in personal credit risk evaluation. In the SHAP value, we can see consumption ability and average quota utilization have a positive impact on credit risk, and consumption ability has a strong correlation with credit risk. Active days, days of transaction, and maximum quota utilization have a negative impact on credit risk, and maximum quota utilization has a strong correlation with credit risk. It not only supplements the indicators beyond the traditional credit information, but also improves the accuracy of personal credit risk evaluation.

5. Discussion

In this study, we investigate the previous studies on personal credit risk evaluation. We also categorize the evaluation of personal credit risk from the perspective of indicators and models. The findings are as follows. First, in many evaluation methods literature, personal credit risk evaluation is considered as a modeling problem. Second, in the selection of personal credit risk evaluation indicators, personal consumption information is rarely or often ignored. Thirdly, in many cases, machine learning method can be used as a supplement to logistic regression.

Our findings also suggest the effect of consumer information in personal credit risk assessment. First, personal consumer loans will affect customers' intertemporal consumption behavior. Second, "soft information," which is different from customer's basic information, is equally important for identifying personal credit risk. Finally, through the empirical evaluation of personal credit risk model, we can find

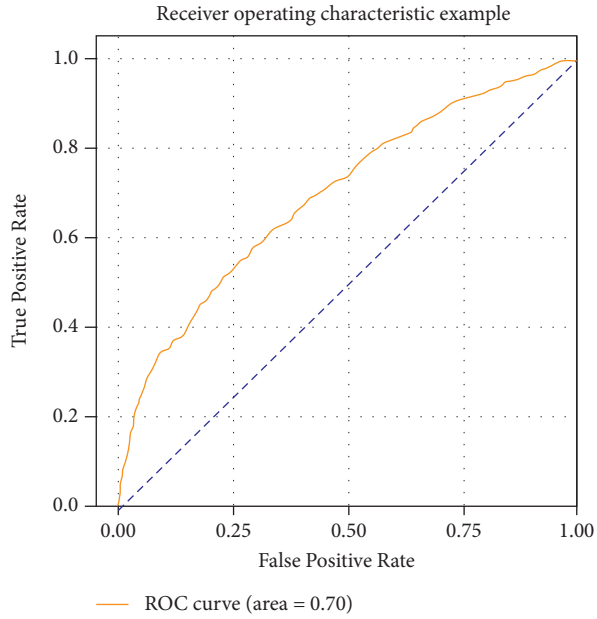

Figure 1: Prediction results of model 1.

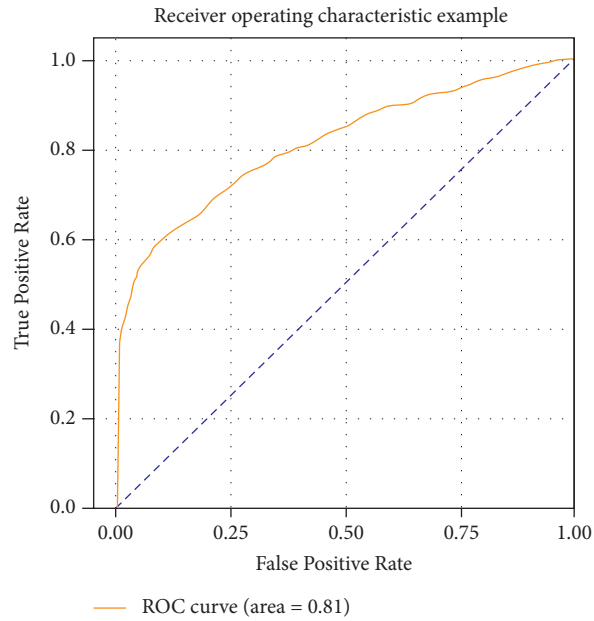

Figure 2: Prediction results of model 5.

more accurate consumer credit value. Of course, the prevention of personal credit risk not only stays in the evaluation, but should be able to provide clues on how to avoid default.

This study has several limitations. We do not cover all the consumer information of borrowers. Information that may affect customer consumption is not considered. Although we sort out the literature on personal credit risk assessment, we do not cover all the literature, but introduce the representative research in each aspect. Through this concentration, we come to meaningful findings and insights related to this topic.

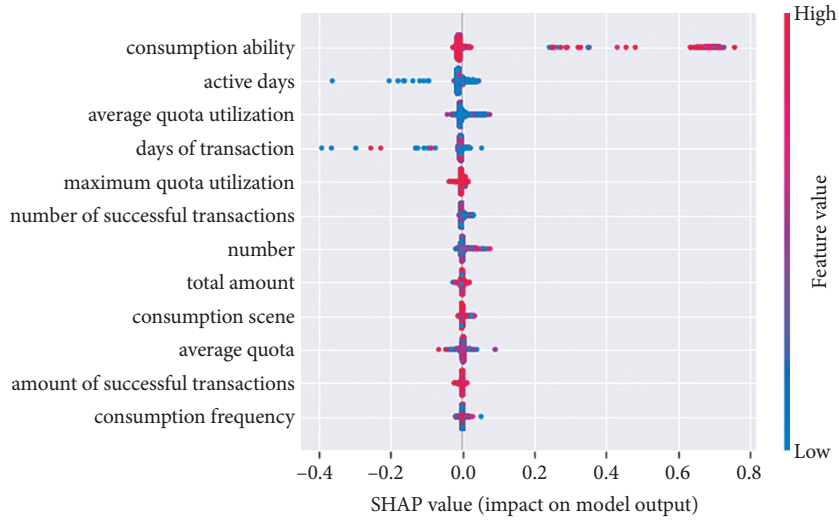

Figure 3: Feature importance and SHAP value plot.

6. Conclusions

Through the empirical analysis of personal credit risk evaluation, this paper describes the characteristics and influencing factors of consumption information and proves the value and effect of consumption information in personal credit risk evaluation. In order to alleviate the long-term credit constraints, it is necessary to promote the development of the credit market on the premise of meeting the loan needs of tail customers. With the strong promotion of financial technology, Internet credit products came into being. However, the current credit investigation system cannot cover all the information of loan demanders, and the credit risk evaluation results are inaccurate. Therefore, how to evaluate credit risk effectively has become an urgent problem to be solved. This requires financial institutions to seek information that can widely cover all loan demanders objectively. Different from the traditional credit information, consumer information has the characteristics of easy access and prominent preference, which can be used as an effective supplement to the traditional credit information. Evaluation of the effect of consumer information effective has become the focus of attention in personal credit risk evaluation.

This paper selects the borrower information from a Chinese platform that has both online shopping and consumer loan as a sample. We use logistic regression model, LightGBM algorithm, and Shapley additive explanation to analyze the value and effect of traditional credit information and consumption information in personal credit risk evaluation. The conclusions are as follows: the information of credit card use can predict the borrower's repayment behavior effectively and provide effective support for personal credit risk evaluation. The consumption information of the platform and the transaction information of the platform can predict the borrower's repayment behavior effectively and provide effective support for personal credit risk evaluation. The predictive model accuracy of ROC curve has proved that adding consumption information to the model can improve the accuracy of the model effectively. The importance of model variables is ranked, and there are 5 consumption indicators in the first 5 indicators, which further verifies the value and effect of consumption information in personal credit risk evaluation. Shapley addition explanation also confirmed the influence and contribution of consumption information to personal credit risk. This study not only reveals the effect and value of consumer information in personal credit risk evaluation effectively, but also provides new ideas for the development of consumer financial market.

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.

References

[1] J. Duarte, S. Siegel, and L. Young, "Trust and credit: the role of appearance in peer-to-peer lending," *Review of Financial Studies*, vol. 25, no. 8, pp. 2455–2484, 2012.

[2] M. Y. Song, "A literature review on the latest research of consumer finance in China. Contemp," *Contemporary Economic Management*, vol. 37, no. 4, pp. 6–12, 2015.

[3] Z. Wang, C. Zhou, L. Liao, and W. Zhang, "Informational content of consumption behavior in consumer credit risk evaluation," *Economic Research Journal*, vol. 55, no. 1, pp. 149–163, 2020.

[4] J. E. Stiglitz and A. Weiss, "Credit rationing in markets with imperfect information," *The American Economic Review*, vol. 71, no. 3, pp. 393–410, 1981.

[5] A. Sufi, "Information asymmetry and financing arrangements: evidence from syndicated loans," *The Journal of Finance*, vol. 62, no. 2, pp. 629–668, 2007.

[6] M. Klafft, "Peer to peer lending: auctioning microcredits over the internet," in *Proceedings of the International Conference on Information Systems*, Technology and Management, Dubai, March 2008.

[7] G. Zhou, D. Ruan, and C. Fan, "Loan-reduction and crowding-out effects in asymmetric-information credit markets," *Finance Forum*, vol. 26, no. 1, pp. 25–36, 2021.

[8] J. C. Stein, "Information production and capital allocation: decentralized versus hierarchical firms," *The Journal of Finance*, vol. 57, no. 5, pp. 1891–1921, 2002.

[9] S. Li and X. Ji, "The application of the Lasso-Cox model in personal credit risk assessment," *Resource Development & Market*, vol. 37, no. 2, pp. 129–135, 2021.

[10] T. Hildebrand, M. Puri, and J. Rocholl, "Adverse incentives in crowdfunding," *Management Science*, vol. 63, no. 3, pp. 587–608, 2017.

[11] M. Lin, N. R. Prabhala, and S. Viswanathan, "Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending," *Management Science*, vol. 59, no. 1, pp. 17–35, 2013.

[12] Y. Su and C. Cheng, "An empirical study on the influencing factors of P2P online borrowers' default Behavior," *Journal of Financial Development Research*, vol. 1, pp. 70–76, 2017.

[13] G. Chi, Y. Zhang, and B. Shi, "The debt rating for small enterprises based on Probit regression," *Journal of Management Sciences in China*, vol. 19, no. 6, pp. 136–156, 2016.

[14] R. Emekter, Y. Tu, B. Jirasakuldech, and M. Lu, "Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending," *Applied Economics*, vol. 47, no. 1, pp. 54–70, 2015.

[15] M. J. Garmaise and G. Natividad, "Consumer default, credit reporting, and borrowing constraints," *The Journal of Finance*, vol. 72, no. 5, pp. 2331–2368, 2017.

[16] Y. Q. Xu and M. Q. Pan, "Application of analytic hierarchy process and support vector machine in personal credit evaluation," *Chinese Journal of Management Science*, vol. 24, no. S1, pp. 106–112, 2016.

[17] J. A. Ohlson, "Financial ratios and the probabilistic prediction of bankruptcy," *Journal of Accounting Research*, vol. 18, no. 1, pp. 109–131, 1980.

[18] D. W. Hosmer and S. Lemeshow, *Applied Logistic Regression*, Wiley, New Jersey, USA, 2nd ed edition, 2000.

[19] G. Kordas, "Credit scoring using binary quantile regression," in *Statistical Data Analysis Based on the L1-Norm and Related Methods,"*, Y. Dodge, Ed., Springer, Berlin, Germany, pp. 125–137, 2002.

[20] M. Du, L. Li, and X. Zhang, "Research on P2P credit risk prediction based on two-step subsampling algorithm," *Journal of Systems Science and Mathematical Sciences*, vol. 41, no. 2, pp. 566–576, 2021.

[21] X. Liu and W. Wang, "A comparative study on three models for credit risk identification in Chinese commercial banks," *Economic Survey*, vol. 32, no. 6, pp. 132–137, 2015.

[22] Z. Khemais, D. Nesrine, and M. Mohamed, "Credit scoring and default risk prediction: a comparative study between discriminant analysis & logistic regression," *International Journal of Economics and Finance*, vol. 8, no. 4, pp. 39–53, 2016.

[23] T. Cheng and Y. Wen, "Probability of default measurement study for individual client of margin trading and securities lending business," *Journal of Financial Research*, vol. 41, no. 4, pp. 174–189, 2016.

[24] F. Luo and X. Chen, "Credit risk assessment of personal small loan based on logistic regression model and its application," *The Theory and Practice of Finance and Economics*, vol. 38, no. 1, pp. 30–35, 2017.

[25] S. Hu, H. Lei, and H Hu, "Research on credit risk measurement of China's real estate enterprises based on logistic model," *China Soft Science*, vol. 12, pp. 157–164, 2018.

[26] M. Jiang, P. Xu, X. Ren, and K. Che, "Research on algorithms development and optimization for personal credit scoring," *Journal of Harbin Institute of Technology*, vol. 47, no. 5, pp. 40–45, 2015.

[27] M. Verleysen and D. Francois, "The curse of dimensionality in data mining and time series prediction," in *Proceedings of the Neural Networks*, pp. 758–770, Barcelona, Spain, June 2005.

[28] M. E. Houle, H.-P. Kriegel, P. Kröger, E. Schubert, and A. Zimek, "Can shared-neighbor distances defeat the curse of dimensionality," in *Proceedings of the international Conference on Scientific and Statistical Database Management*, pp. 482–500, SSDBM), Heidelberg, Germany, January 2010.

[29] M. Bertrand and E. Kamenica, "Coming apart? cultural distances in the United States over time," in *Proceedings of the NBER Working Pap*, Chicago, IL, USA, June 2018.

[30] S. Belenzon, A. K. Chatterji, and B. Daley, "Eponymous entrepreneurs," *The American Economic Review*, vol. 107, no. 6, pp. 1638–1655, 2017.

[31] J. Guzman and S. Stern, *The State of American Entrepreneurship: New Estimates of the Quantity and Quality of Entrepreneurship for 15 US States, 1988-2014*, NBER Working Pap, Cambridge USA, 2016.

[32] M. Pagano and T. Jappelli, "Information sharing in credit markets," *The Journal of Finance*, vol. 48, no. 5, pp. 1693–1718, 1993.

[33] S. Djankov, C. McLiesh, and A. Shleifer, "Private credit in 129 countries☆," *Journal of Financial Economics*, vol. 84, no. 2, pp. 299–329, 2007.

[34] T. Beck, A. Demirguc-Kunt, and P. Honohan, "Access to financial services: measurement, impact, and policies," *The World Bank Research Observer*, vol. 24, no. 1, pp. 119–145, 2009.

[35] M. Brown, T. Jappelli, and M. Pagano, "Information sharing and credit: firm-level evidence from transition countries," *Journal of Financial Intermediation*, vol. 18, no. 2, pp. 151–172, 2009.

[36] T. Berg, V. Burg, A. Gombović, and M. Puri, "On the rise of fintechs – credit scoring using digital footprints," *Review of Financial Studies*, vol. 33, no. 7, 2018.

[37] H. Noh, T. Roh, and I. Han, "Prognostic personal credit risk model considering censored information," *Expert Systems with Applications*, vol. 28, no. 4, pp. 753–762, 2005.

[38] S. Agarwal, P. M. Skiba, and J. Tobacman, "Payday loans and credit cards: new liquidity and credit scoring puzzles?" *The American Economic Review*, vol. 99, no. 2, pp. 412–417, 2009.

[39] Z. Mo, C. F. Zhang, W. Wei, D. C. You, and S. Zhang, "Research on personal credit risk assessment method based on bagging integration," *Systems Engineering*, vol. 37, no. 1, pp. 143–151, 2019.

[40] J. Mallick, S. Alqadhi, S. Talukdar et al., "Risk assessment of resources exposed to rainfall induced landslide with the development of GIS and RS based ensemble metaheuristic machine learning algorithms," *Sustainability*, vol. 13, no. 2, p. 457, 2021.

[41] K. Ye, "Research on personal credit risk assessment based on machine learning algorithm," *International Journal of Intelligence Science*, vol. 6, no. 1, pp. 146–156, 2020.

[42] M. Wang and H. Yang, "Research on personal credit risk assessment model based on instance-based transfer learning," *International Journal of Intelligence Science*, vol. 11, no. 01, pp. 44–55, 2021.

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Research Article

Forecasting Renminbi Exchange Rate Volatility Using CARR-MIDAS Model

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In this study, we propose to employ the conditional autoregressive range-mixed-data sampling (CARR-MIDAS) model to model and forecast the renminbi exchange rate volatility. The CARR-MIDAS model exploits intraday information from the intraday high and low prices, which has the capacity to capture the high persistence of conditional range (volatility). The empirical results show that the range-based CARR-MIDAS model provides more accurate out-of-sample forecasts of the renminbi exchange rate volatility compared to the return-based GARCH and GARCH-MIDAS models and the range-based CARR model for forecast horizons of 1 day up to 3 months. In addition, the superior predictive ability of the CARR-MIDAS model is robust to different forecast windows. Hence, our CARR-MIDAS model provides a promising tool for forecasting the renminbi exchange rate volatility.

1. Introduction

Modeling and forecasting financial market volatility have attracted a great deal of attention in the financial econometric literature due to its important role in many financial applications, such as portfolio allocation, risk management, and option pricing. In the past decades, numerous volatility models have been developed to model and forecast the dynamics of the volatility process. The generalized autoregressive conditional heteroskedasticity (GARCH) model by Bollerslev [1] is among the most popular volatility models. However, the GARCH model is a return-based model that uses only closing prices to estimate volatility and fails to exploit the intraday information.

An alternative approach for estimating volatility is to use the daily intraday range from the intraday high and low prices. It is clear that the range contains more information about intraday price movements than the traditional return-based volatility estimator that is based on a single measurement of the closing price. It has been documented in the literature that the range is a more efficient volatility estimator than the return-based one (see, e.g., [2–5] and Chou [6] propose a range-based volatility model: the conditional autoregressive range (CARR) model, and show that the model provides more accurate volatility estimates than the traditional return-based GARCH model. Since then, the CARR model has received considerable attention in the literature (see, e.g., [7–16]).

Despite the empirical success of the CARR model, the model with a constant long-run trend of the range is still not adequate to account for the high persistence (long memory) of the conditional range (volatility). To address this issue, an extension of the CARR model, namely, the CARR-mixed-data sampling (CARR-MIDAS) model has been proposed by Wu et al. [17]. The CARR-MIDAS model inherits the strength of the range-based CARR model and its capacity to exploit intraday information for estimating volatility. Most importantly, the CARR-MIDAS model features a multiplicative decomposition of the conditional range into a short-run and a long-run component, where the short-run component is governed by a CARR(1,1) process, while the long-run component is modeled using a MIDAS approach. The multiplicative component structures have been recently proposed by Engle and Rangel [18]; Engle et al. [19], and Amado and Teräsvirta [20, 21] in the context of the return-based GARCH framework. It is claimed that this structure is

useful to capture complex volatility dynamics such as the high persistence of volatility and to well handle the structural changes or nonstationarities in volatility [22, 23]. Our proposed CARR-MIDAS model is motivated by the multiplicative component GARCH-MIDAS model of Engle et al. [19], which allows to capture time-varying long-run trends in volatility through a parsimonious and flexible MIDAS structure.

While Wu et al. [17] employ the CARR-MIDAS model to investigate the impact and predictive power of EPU on the Chinese stock market volatility, in this study we apply the model to forecast the renminbi exchange rate volatility. To the best of our knowledge, the usefulness of the CARR-MIDAS model for forecasting the renminbi exchange rate volatility has not been investigated in the literature. Since the implementation of the renminbi exchange rate regime reform in 2005, the renminbi exchange rate has experienced significant fluctuations. Forecasting the renminbi exchange rate volatility is crucial as it has an important impact on international trade and economic growth. We examine and compare the out-of-sample forecast performance of the range-based CARR-MIDAS model with that of the two popular return-based volatility models: the GARCH model of Bollerslev [1] and the GARCH-MIDAS model of Engle et al. [19], and the range-based CARR model of Chou [6]. Our results show that the CARR-MIDAS model provides more accurate out-of-sample forecasts of the renminbi exchange rate volatility compared to the return-based GARCH and GARCH-MIDAS models and the range-based CARR model for forecast horizons of 1 day up to 3 months. We also find that the superior forecast ability of the CARR-MIDAS model is robust to different forecasting windows. These results highlight the value of incorporating the intraday range and a MIDAS component (long-run component) into the volatility model for forecasting the renminbi exchange rate volatility.

The remainder of this study is organized as follows. In Section 2, we introduce the CARR-MIDAS model. In Section 3, we illustrate the forecast evaluation method. Section 4 presents the empirical results, while Section 5 concludes the study.

2. The Model

In this study, we utilize the intraday range to model and forecast the dynamic behavior of the renminbi exchange rate volatility. It has been theoretically shown that the intraday range is a more accurate volatility estimator compared to the realized volatility estimator, which is based on five, or less, equidistance points in time (Degiannakis and Livada, 2013). The intraday range of Parkinson [2] is defined as follows:

$$R_i = \frac{\log(H_i) - \log(L_i)}{\sqrt{4\log(2)}}, \tag{1}$$

where H_i and L_i are the highest and lowest prices observed at day i, respectively. Parkinson [2] shows that the range given by equation (1) is an effective estimator of the volatility and demonstrates the efficiency of this range-based estimator versus traditional volatility estimator based on the close-to-close returns.

2.1. The CARR Model. To describe the dynamics of the range, Chou [6] introduces the CARR model, which can be written as follows:

$$\begin{aligned} R_i &= \lambda_i \varepsilon_i, \varepsilon_i \mid \mathscr{F}_{i-1} \sim \exp(1), \\ \lambda_i &= \omega + \alpha R_{i-1} + \beta \lambda_{i-1}, \end{aligned} \tag{2}$$

where λ_i is the conditional mean of the range based on the information set, $\mathscr{F}_{i-1}$, up to day $i-1$, and $\exp(1)$ is an exponential distribution with unit mean. The coefficients, ω, α, and β, in the conditional mean equation are all assumed to be nonnegative to ensure positivity of the range. Furthermore, the stationary condition for the process is $\alpha + \beta < 1$, where $\alpha + \beta$ determines the persistence of range shocks, and the unconditional (long run) mean of the range is $\omega/(1 - (\alpha + \beta))$.

2.2. The CARR-MIDAS Model. The CARR model is a range-based analog to the traditional return-based GARCH model, which is capable of capturing the well-known phenomenon of volatility clustering. Chou [6] shows that the range-based CARR model outperforms the return-based GARCH model in terms of out-of-sample volatility forecasts. However, the CARR model with a constant long-run trend of the range is still very restrictive and does not account for high persistence (long memory) of conditional volatility. Motivated by the return-based GARCH-MIDAS model of Engle et al. [19], in this study we introduce an extension of the CARR model, namely, the CARR-MIDAS model, which can be written as follows:

$$\begin{aligned} R_{i,t} &= \lambda_{i,t} \varepsilon_{i,t}, \varepsilon_{i,t} \mid \mathscr{F}_{i-1,t} \sim \exp(1), \\ \lambda_{i,t} &= \tau_t g_{i,t}, \\ g_{i,t} &= (1 - \alpha - \beta) + \alpha \frac{R_{i-1,t}}{\tau_t} + \beta g_{i-1,t}, \\ \log(\tau_t) &= m + \theta \sum_{k=1}^{K} \varphi_k(\gamma) \log(RRV_{t-k}), \\ \mathrm{RRV}_t &= \sum_{i=1}^{N_t} R_{i,t}^2, \end{aligned} \tag{3}$$

where $R_{i,t}$ is the range on day i in month t, and $\lambda_{i,t}$ is the conditional mean of the range based on the information set, $\mathscr{F}_{i-1,t}$, up to day $i-1$ of month t, which is multiplicatively decomposed into two components, a short-run component, $g_{i,t}$, and a long-run component, τ_t. The short-run component, $g_{i,t}$, is specified as a CARR(1,1) process, while the long-run component, τ_t, is modeled in the spirit of the MIDAS regression, which is driven by the smoothing monthly realized range volatility (RRV) with the weighting scheme φ_k. To ensure nonnegativity and stationarity for the short-run component $g_{i,t}$, we assume that $\alpha > 0$, $\beta > 0$, and $\alpha + \beta < 1$.

One-parameter beta polynomial is employed as the weighting scheme φ_k due to its parsimony and flexibility:

$$\varphi_k(\gamma) = \frac{(1-k/K)^{\gamma-1}}{\sum_{j=1}^{K}(1-j/K)^{\gamma-1}}, \tag{4}$$

where K is the number of MIDAS lags with $\sum_{k=1}^{K}\varphi_k(\gamma) = 1$.

It is clear that the CARR-MIDAS model is more flexible relative to the CARR model. It is straightforward to show that

$$\lambda_{i,t} = \omega_t + \alpha R_{i-1,t} + \beta\lambda_{i-1,t}, \tag{5}$$

where $\omega_t = (1-\alpha-\beta)\tau_t$ implies a time-varying parameter, which allows to capture structural changes in conditional volatility. Lamoureux and Lastrapes [24] show that structural changes should be taken into account when modeling volatility; otherwise, it may induce spurious apparent persistence (long memory features) in the volatility process. By assuming a constant long-run component, the CARR-MIDAS model reduces to the original CARR model.

2.3. Maximum Likelihood Estimation. The CARR-MIDAS model is easy to estimate. We estimate the CARR-MIDAS model using the quasi-maximum likelihood method. The log-likelihood function of the CARR-MIDAS model can be written as follows:

$$\ell(\Theta) = -\sum_{t=1}^{T}\sum_{i=1}^{N_t}\left[\log\left(\lambda_{i,t}\right) + \frac{R_{i,t}}{\lambda_{i,t}}\right], \tag{6}$$

where $\Theta = (m, \theta, \gamma, \alpha, \beta)'$ is the vector of all model parameters. The maximum likelihood estimators, $\widehat{\Theta}$, can be obtained by maximizing the log-likelihood function in equation (6).

3. Forecast Evaluation

To evaluate the forecast performance of the CARR-MIDAS model, we use two robust loss functions, the mean squared error (MSE), and the quasi-likelihood (QLIKE), which are given as follows:

$$\begin{aligned}\text{MSE}: \text{Loss}_{i,t} &= \left(MV_{i,t} - FV_{i,t}\right)^2,\\ \text{QLIKE}: \text{Loss}_{i,t} &= \log\left(FV_{i,t}\right) + \frac{MV_{i,t}}{FV_{i,t}},\end{aligned} \tag{7}$$

where $MV_{i,t}$ is a measure of the ex-postvolatility, and $FV_{i,t}$ is the forecasted volatility. We use the range given in equation (1) as the ex-postvolatility. Patton [25] shows that the MSE and QLIKE loss functions are robust to imperfect proxy of actual volatility and provide a consistent ranking of forecasts.

We test the significant differences between competing models by employing the model confidence set (MCS) approach of Hansen et al. [26]. Let $\mathscr{M}^0$ be a set of competing models. We identify the set of the best-performing models with a given confidence level α, namely, the MCS $\widehat{\mathscr{M}}^*_{1-\alpha}$. MCS approach tests the null hypothesis of equal forecasting accuracy:

$$H_{0,\mathscr{M}}: E\left(d_{uv,i,t}\right) = 0, \quad \forall u, v \in \mathscr{M}, \mathscr{M} \subset \mathscr{M}^0, \tag{8}$$

where $d_{uv,i,t} \equiv \text{Loss}_{i,t}(u) - \text{Loss}_{i,t}(v)$ denotes the difference in the MSE or QLIKE loss of models u and v. If the null hypothesis $H_{0,\mathscr{M}}$ is rejected, the worst-performing model from the set $\mathscr{M}$ is eliminated. The procedure is iteratively performed, until no further model can be eliminated. The final set of surviving models is denoted by $\widehat{\mathscr{M}}^*_{1-\alpha}$. Following Hansen et al. [26], we implement the MCS procedure using a block bootstrap of 10^5 replications and a significance level of $\alpha = 10\%$.

Moreover, we examine the significance of the difference between the competing models for volatility forecasting using the Diebold and Mariano [27] test. We test the superiority of model u over model v using a t-test for the coefficient $d_{u,v}$ in the following:

$$\left(MV_{i,t} - FV_{i,t}(u)\right)^2 - \left(MV_{i,t} - FV_{i,t}(v)\right)^2 = d_{u,v} + \eta_{i,t}. \tag{9}$$

A significantly positive $d_{u,v}$ indicates that the model v dominates the model u and vice versa.

4. Empirical Results

4.1. Data. The data used in the study consist of daily open, high, low, and close prices for the renminbi exchange rate of the Chinese Yuan (CNY) against the US Dollar (USD). The exchange rate is measured as CNY of one unit of USD. The data are obtained from the Wind Database of China for the period January 2, 2006, to December 31, 2020, for a total of 3,716 trading days. Daily intraday ranges are calculated using the equation (1). For comparison, we also compute the daily log returns as $r_i = \log(P_i/P_{i-1})$, where P_i is the closing price on day i. Figure 1 plots the daily returns, ranges for the USD/CNY exchange rate, and shows that the well-known behaviors of volatility clustering in the USD/CNY exchange rate are apparent. It is also worth noting that the USD/CNY exchange rate experienced significant fluctuations, particularly in recent years.

Table 1 presents descriptive statistics for the USD/CNY daily return and range series and the series of the absolute return. The three series exhibit positive skewness and leptokurtosis, and the Jarque–Bera statistics show that all the three series fail the normality assumption. The Ljung-Box Q statistics up to 12 lags for the absolute return and range series show the existence of high persistence (serial correlation) of the USD/CNY exchange rate volatility. In particular, the obviously larger Ljung-Box Q statistic for the range series than for the absolute return series suggests a much higher persistence in the USD/CNY volatility for the range than for the absolute return series. Our proposed CARR-MIDAS model aims to capture this high degree of persistence by assuming a MIDAS component (long-run component) for the conditional range of the USD/CNY exchange rate.

4.2. Estimation Results. Table 2 reports the estimation results for the CARR-MIDAS model. In addition, estimates for the CARR model of Chou [6] are presented for the purpose of

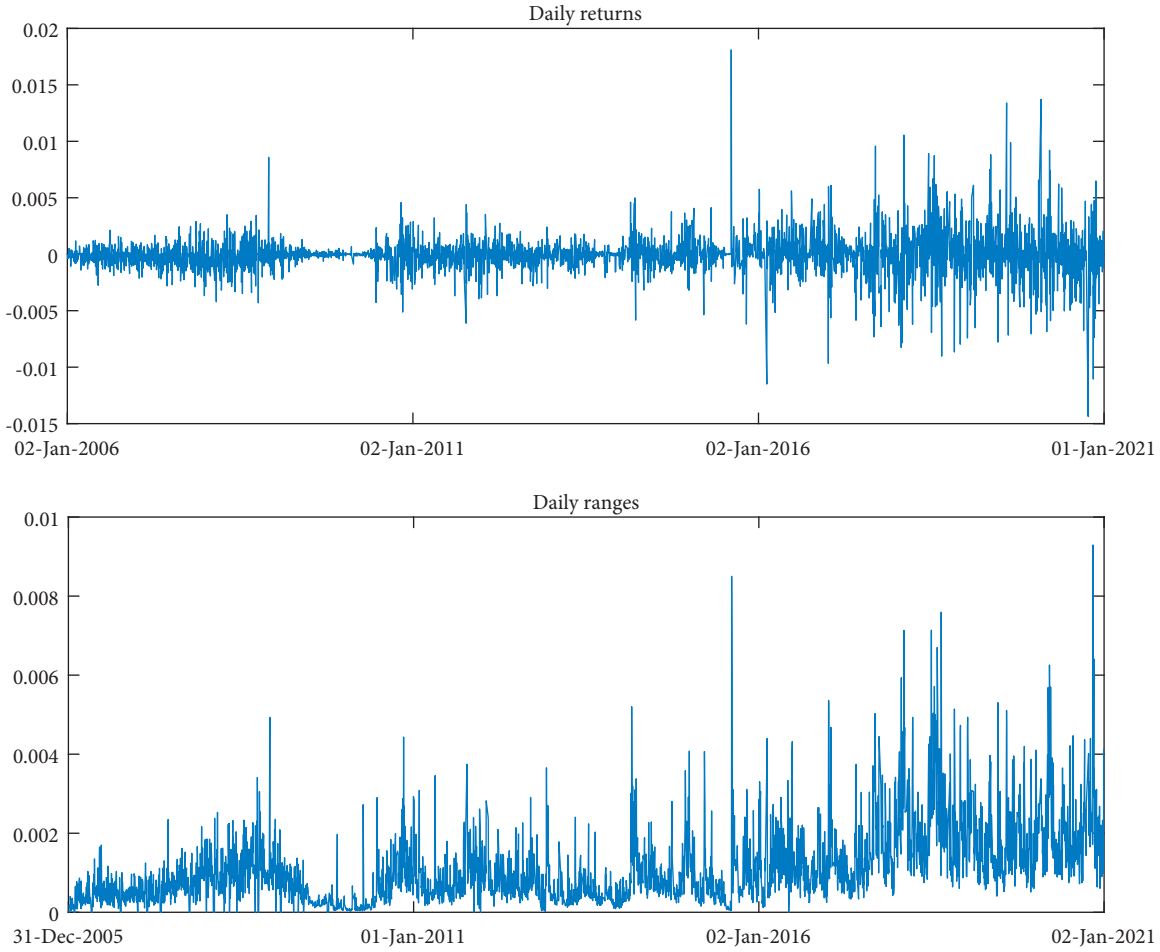

Figure 1: USD/CNY daily returns and ranges for the period January 2, 2006, to December 31, 2020.

Table 1: Descriptive statistics for the USD/CNY daily returns and ranges for the period January 2, 2006, to December 31, 2020.

	Return	Absolute return	Range
Mean	−0.0001	0.0010	0.0011
Min.	−0.0144	0.0000	0.0000
Max.	0.0181	0.0181	0.0093
Std. Dev.	0.0017	0.0014	0.0009
Skewness	0.4067	3.5882	2.1745
Kurtosis	15.9693	24.8488	10.7412
Jarque–Bera	26138.8708	81865.2329	12207.1151
Q(12)	36.9645	2015.4260	11143.1941

Note: Q(12) is the Ljung-Box statistic for autocorrelation up to 12 lags.

Table 2: Estimation results.

Parameter	CARR	CARR-MIDAS
m (ω)	0.0000 (0.0000)	−2.3302 (0.0255)
θ	—	0.4256 (0.0032)
γ	—	15.3240 (0.2479)
α	0.2925 (0.0108)	0.4000 (0.0134)
β	0.6693 (0.0104)	0.3717 (0.0160)
$\alpha + \beta$	0.9618	0.7716
Log-lik	22397.4605	22434.3209
AIC	−44788.9210	−44858.6417
BIC	−44770.2598	−44827.5397

Note: Log-lik is the log-likelihood, AIC is the Akaike information criterion, and BIC is the Bayesian information criterion. The numbers in parentheses are asymptotic standard errors for the model parameters.

comparison. For the CARR-MIDAS specification, we employ three MIDAS lag years, i.e., we choose $K = 36$. Conrad and Kleen [23] show that the data will identify the optimal weighting scheme as long as K is chosen reasonably large.

It can be seen from Table 2 that the estimate of the persistence coefficient $\alpha + \beta$ in the CARR model is close to one, showing high persistence in the conditional range process. Note also that in the CARR-MIDAS estimation results, the estimate of the persistence coefficient of the short-run component, $\alpha + \beta$, is less than one, with its magnitude obviously smaller than that of the CARR (0.7716 vs. 0.9618), indicating that accounting for the long-run component reduces persistence in the short-run component. Additionally, the estimate of the parameter θ is significant positive, which suggests the presence of the MIDAS component (long-run component), and the monthly RRV is positively related to the long-run component. Figure 2 plots the conditional range $(\lambda_{i,t})$ along with the long-run component (τ_t) and the short-run component $(g_{i,t})$ from the CARR-MIDAS model. The long-term component appears smooth and tracks secular volatility trends over the sample

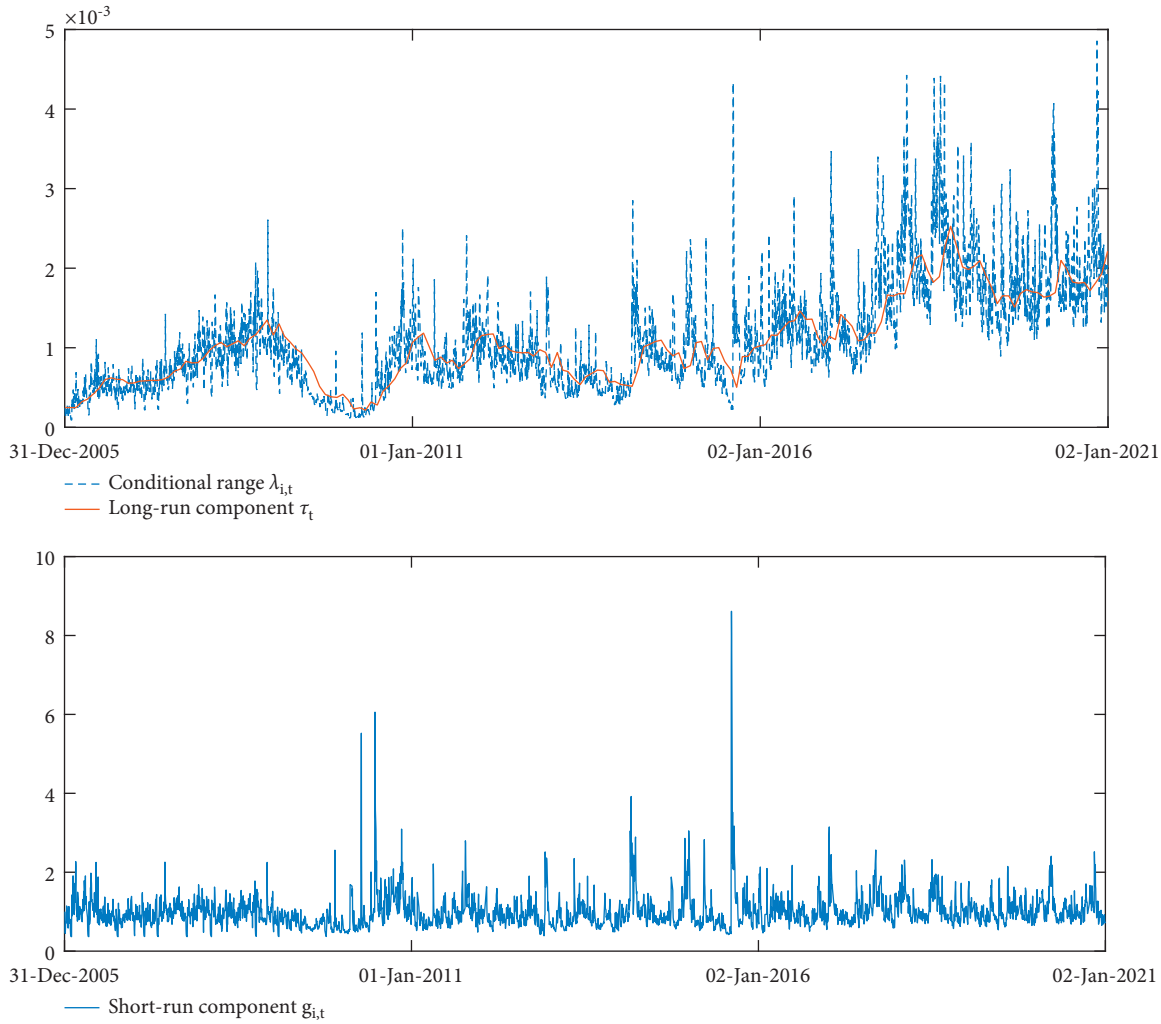

FIGURE 2: Conditional range ($\lambda_{i,t}$) and its long-term component (τ_t) and short-run component ($g_{i,t}$) from the CARR-MIDAS model.

period, while the short-run component exhibits the mean reverting property (reverts to a long-run mean of one).

According to the values of the log-likelihood, the Akaike and Bayesian information criteria shown in Table 2, the CARR-MIDAS model fits the data better compared to the CARR model. This result highlights the importance of incorporating the MIDAS component (long-run component) for modeling the renminbi exchange rate volatility.

4.3. Out-of-Sample Results. In this section, we investigate the out-of-sample forecast performance of the CARR-MIDAS model in forecasting the renminbi exchange rate volatility. We compare the performance of the range-based CARR-MIDAS model with that of the two popular return-based volatility models: the GARCH model of Bollerslev [1] and the GARCH-MIDAS model of Engle et al. [19], and the range-based CARR model of Chou [6]. We employ a rolling window scheme to perform the out-of-sample forecasts. In particular, we estimate model parameters on a rolling basis with 3,000 observations and leave the remaining (716) observations for out-of-sample evaluation. The forecast horizon is set to one day (1d), two days (2d), three days (3d), four days (4d), one week (1w), two weeks (2w), one month (1m), two months (2m), and three months (3m), i.e., 1 day, 2 days, 3 days, 4 days, 5 days, 10 days, 22 days, 44 days, and 66 days ahead forecasts.

Table 3 reports the out-of-sample forecast evaluation results. It can be seen from the table that the range-based CARR (CARR-MIDAS) model generally outperforms the return-based GARCH (GARCH-MIDAS) model for the nine forecast horizons in terms of the MSE and QLIKE loss functions, which highlights the value of employing the intraday range for forecasting the renminbi exchange rate volatility. Moreover, we find that the GARCH-MIDAS (CARR-MIDAS) model improves upon the forecasting performance of the original GARCH (CARR) model for all forecast horizons. As the forecast horizon increases, the improvements appear to grow. These findings illustrate that incorporating the MIDAS component (long-run component) is important for improving the volatility forecasts, particularly for longer forecast horizons. In summary, the CARR-MIDAS model gives the lowest loss values for all forecast horizons and is clearly the preferred and best model for forecasting the renminbi exchange rate volatility.

Table 3: Out-of-sample forecast evaluation results.

Horizon	GARCH	GARCH-MIDAS	CARR	CARR-MIDAS
Panel A: MSE loss function				
1d	1.8812 $E-06$	1.6093 $E-06$	1.0439 $E-06$	**1.0100 E – 06**
2d	2.0191 $E-06$	1.6917 $E-06$	1.2202 $E-06$	**1.1935 E – 06**
3d	2.1171 $E-06$	1.7454 $E-06$	1.2792 $E-06$	**1.2428 E – 06**
4d	2.1787 $E-06$	1.7707 $E-06$	1.3163 $E-06$	**1.2705E – 06**
1w	2.2375 $E-06$	1.7879 $E-06$	1.3601 $E-06$	**1.2956 E – 06**
2w	2.4510 $E-06$	1.8444 $E-06$	1.6051 $E-06$	**1.4181 E – 06**
1m	2.9237 $E-06$	1.8923 $E-06$	2.0200 $E-06$	**1.4109 E – 06**
2m	4.3222 $E-06$	2.2110 $E-06$	2.4252 $E-06$	**1.3921 E – 06**
3m	5.5743 $E-06$	2.1918 $E-06$	2.5807 $E-06$	**1.3845 E – 06**
Panel B: QLIKE loss function				
1d	−5.1629	−5.1733	−5.2063	**−5.2171**
2d	−5.1539	−5.1672	−5.1782	**−5.1961**
3d	−5.1485	−5.1637	−5.1687	**−5.1920**
4d	−5.1457	−5.1628	−5.1617	**−5.1909**
1w	−5.1440	−5.1629	−5.1510	**−5.1880**
2w	−5.1362	−5.1611	−5.1023	**−5.1728**
1m	−5.1270	−5.1677	−4.9900	**−5.1788**
2m	−5.0712	−5.1431	−4.8115	**−5.1863**
3m	−5.0353	−5.1448	−4.7389	**−5.1908**

Note: MSE is the mean squared error, and QLIKE is the quasi-likelihood. Bold entries indicate the model with the lowest loss value per horizon (in each row). Shaded entries indicate the model includes the MCS at a 10% significance level. For the forecast horizons, d = day, w= week, and m = month.

Table 4: Diebold-Mariano statistics.

Horizon		CARR	GARCH-MIDAS	GARCH
1d	CARR-MIDAS	1.8760	8.3026	9.7510
	CARR		7.6976	9.3290
	GARCH-MIDAS			10.4591
2d	CARR-MIDAS	1.1952	6.1360	8.0666
	CARR		5.7277	7.8760
	GARCH-MIDAS			11.3301
3d	CARR-MIDAS	1.3302	5.7830	7.8312
	CARR		5.3741	7.6804
	GARCH-MIDAS			11.5681
4d	CARR-MIDAS	1.4811	5.4140	7.5467
	CARR		4.9367	7.3325
	GARCH-MIDAS			11.7271
1w	CARR-MIDAS	1.9078	5.0917	7.4106
	CARR		4.4220	7.0158
	GARCH-MIDAS			12.1817
2w	CARR-MIDAS	4.9525	3.8211	6.8328
	CARR		1.9808	5.3129
	GARCH-MIDAS			13.1066
1m	CARR-MIDAS	13.0779	4.3357	8.8228
	CARR		-0.8880	4.4641
	GARCH-MIDAS			15.1071
2m	CARR-MIDAS	15.0205	9.3679	14.9260
	CARR		-1.4974	7.6723
	GARCH-MIDAS			18.1445
3m	CARR-MIDAS	15.5806	8.9919	15.9034
	CARR		-2.5555	9.3778
	GARCH-MIDAS			18.7436

Note: A positive statistic indicates that the model in the row dominates the model in the column, and a negative statistic indicates that the model in the column dominates the model in the row. For the forecast horizons, d = day, w = week, and m = month.

The shaded entries in Table 3 identify the model included in the MCS at the significance level of 10%. The results show that the CARR-MIDAS model is included in the MCS for all forecast horizons, and in most cases, it is the only model that is included in the MCS, suggesting that the CARR-MIDAS model significantly outperforms all other models.

Table 4 reports Diebold-Mariano test statistics for all pairs of the four volatility models over the nine different

Table 5: Out-of-sample forecast evaluation results for forecast window of 500.

Horizon	GARCH	GARCH-MIDAS	CARR	CARR-MIDAS
Panel A: MSE loss function				
1d	2.0068 $E-06$	1.6990 $E-06$	9.0186 $E-07$	**8.6854 E − 07**
2d	2.1629 $E-06$	1.7962 $E-06$	1.0384 $E-06$	**9.9931 E − 07**
3d	2.2868 $E-06$	1.8680 $E-06$	1.0871 $E-06$	**1.0256 E − 06**
4d	2.3687 $E-06$	1.9056 $E-06$	1.1331 $E-06$	**1.0539 E − 06**
1w	2.4308 $E-06$	1.9265 $E-06$	1.1882 $E-06$	**1.0895 E − 06**
2w	2.6363 $E-06$	1.9515 $E-06$	1.3307 $E-06$	**1.1545 E − 06**
1m	3.0896 $E-06$	1.9259 $E-06$	1.5823 $E-06$	**1.1650 E − 06**
2m	4.3618 $E-06$	2.1107 $E-06$	1.8549 $E-06$	**1.1911 E − 06**
3m	5.5636 $E-06$	2.0560 $E-06$	2.0134 $E-06$	**1.2128 E − 06**
Panel B: QLIKE loss function				
1d	−5.2147	−5.2273	−5.2764	**−5.2867**
2d	−5.2055	−5.2205	−5.2535	**−5.2707**
3d	−5.1996	−5.2167	−5.2467	**−5.2695**
4d	−5.1950	−5.2143	−5.2391	**−5.2680**
1w	−5.1906	−5.2117	−5.2279	**−5.2625**
2w	−5.1804	−5.2092	−5.1952	**−5.2534**
1m	−5.1659	−5.2144	−5.1322	**−5.2532**
2m	−5.1183	−5.2024	−5.0378	**−5.2602**
3m	-5.0770	−5.1996	−4.9712	**−5.2538**

Note: MSE is the mean squared error, and QLIKE is the quasi-likelihood. Bold entries indicate the model with the lowest loss value per horizon (in each row). Shaded entries indicate the model includes the MCS at a 10% significance level. For the forecast horizons, d = day, w = week, and m = month.

Table 6: Out-of-sample forecast evaluation results for forecast window of 1,000.

Horizon	GARCH	GARCH-MIDAS	CARR	CARR-MIDAS
Panel A: MSE loss function				
1d	1.6488 $E-06$	1.4435 $E-06$	9.3247 $E-07$	**8.9878 E − 07**
2d	1.7634 $E-06$	1.5265 $E-06$	1.1026 $E-06$	**1.0841 E − 06**
3d	1.8302 $E-06$	1.5694 $E-06$	1.1623 $E-06$	**1.1379 E − 06**
4d	1.8754 $E-06$	1.5939 $E-06$	1.2060 $E-06$	**1.1746 E − 06**
1w	1.9301 $E-06$	1.6259$E-06$	1.2743 $E-06$	**1.2281 E − 06**
2w	2.0993 $E-06$	1.6973 $E-06$	1.5302 $E-06$	**1.3638 E − 06**
1m	2.4848 $E-06$	1.8318 $E-06$	2.0408 $E-06$	**1.4434 E − 06**
2m	3.3213 $E-06$	2.0724 $E-06$	2.3934 $E-06$	**1.4053 E − 06**
3m	3.8112 $E-06$	1.9729 $E-06$	2.5319 $E-06$	**1.4155 E − 06**
Panel B: QLIKE loss function				
1d	−5.2591	−5.2696	−5.3043	**−5.3150**
2d	−5.2495	−5.2615	−5.2714	**−5.2880**
3d	−5.2431	−5.2564	−5.2571	**−5.2801**
4d	−5.2391	−5.2535	−5.2470	**−5.2754**
1w	−5.2345	−5.2499	−5.2314	**−5.2660**
2w	−5.2238	**−5.2431**	−5.1694	−5.2402
1m	−5.1942	**−5.2218**	−5.0010	−5.2156
2m	−5.1519	−5.1964	−4.8021	**−5.2212**
3m	−5.1284	−5.1926	−4.7188	**−5.2122**

Note: MSE is the mean squared error, and QLIKE is the quasi-likelihood. Bold entries indicate the model with the lowest loss value per horizon (in each row). Shaded entries indicate the model includes the MCS at a 10% significance level. For the forecast horizons, d = day, w = week, and m = month.

forecast horizons. It can be seen from the table that the differences in forecast accuracy among the four models are significant in most cases, and the significance tends to increase as the forecast horizon increases. In particular, the Diebold-Mariano statistics for the CARR-MIDAS model are unanimously reported to be positive and significant in most cases, which indicates that the CARR-MIDAS model significantly dominates the other models.

4.4. Robustness Check. For the robustness check, the out-of-sample forecast is also performed over different forecast windows (out-of-sample periods). We consider three different forecast windows, 500, 1,000, and 1,500. The out-of-sample forecast evaluation results are presented in Tables 5–7 for the three forecast windows, respectively. As is consistent with the results in Tables 3 and 4, the CARR-MIDAS model significantly outperforms the other models.

Table 7: Out-of-sample forecast evaluation results for forecast window of 1,500.

Horizon	GARCH	GARCH-MIDAS	CARR	CARR-MIDAS
Panel A: MSE loss function				
1d	1.5384 $E-06$	1.3723 $E-06$	8.2349 $E-07$	**7.8460 E − 07**
2d	1.6969 $E-06$	1.4975 $E-06$	**9.5137 E − 07**	9.6109 $E-07$
3d	1.7951 $E-06$	1.5689 $E-06$	**9.9754 E − 07**	1.0141 $E-06$
4d	1.8409 $E-06$	1.5924 $E-06$	**1.0223 E − 06**	1.0430 $E-06$
1w	1.8853 $E-06$	1.6136 $E-06$	**1.0535 E − 06**	1.0800 $E-06$
2w	2.0442 $E-06$	1.6625 $E-06$	**1.1651 E − 06**	1.1862 $E-06$
1m	2.4191 $E-06$	1.7385 $E-06$	1.3695 $E-06$	**1.2373 E − 06**
2m	3.1551 $E-06$	1.8347 $E-06$	1.6240 $E-06$	**1.2379 E − 06**
3m	3.7905 $E-06$	1.7622 $E-06$	1.8127 $E-06$	**1.2149 E − 06**
Panel B: QLIKE loss function				
1d	−5.4350	−5.4477	−5.4963	**−5.5060**
2d	−5.4027	−5.4197	−5.4507	**−5.4637**
3d	−5.3801	−5.4004	−5.4282	**−5.4471**
4d	−5.3742	−5.3955	−5.4241	**−5.4434**
1w	−5.3721	−5.3938	−5.4168	**−5.4353**
2w	−5.3579	−5.3873	−5.3856	**−5.4156**
1m	−5.3368	−5.3762	−5.3529	**−5.4052**
2m	−5.3158	−5.3780	−5.2787	**−5.4077**
3m	−5.2903	−5.3790	−5.1855	**−5.4140**

Note: MSE is the mean squared error, and QLIKE is the quasi-likelihood. Bold entries indicate the model with the lowest loss value per horizon (in each row). Shaded entries indicate the model includes the MCS at a 10% significance level. For the forecast horizons, d = day, w = week, and m = month.

5. Conclusions

In this study, we propose to use the range-based CARR-MIDAS model to modeling and forecasting the renminbi exchange rate volatility. The CARR-MIDAS model exploits intraday information from the intraday high and low prices, and features a multiplicative decomposition of the conditional range into a short-run and a long-run component, where the short-run component is governed by a CARR(1,1) process and the long-run component is modeled by a MIDAS structure, which is capable of capturing the high persistence of conditional range (volatility). To the best of our knowledge, the usefulness of the CARR-MIDAS model for forecasting the renminbi exchange rate volatility has not been investigated in the literature. Empirical results show that the range-based CARR-MIDAS model provides more accurate out-of-sample volatility forecasts compared to the return-based GARCH and GARCH-MIDAS models and the range-based CARR model for forecast horizons ranging from 1 day to 3 months ahead. Moreover, according to the robustness check, the superior predictive ability of the CARR-MIDAS model is robust to different forecast windows. These results highlight the importance of incorporating the intraday range and the MIDAS component (long-run component) for forecasting the renminbi exchange rate volatility. Against the backdrop of repeated shocks to the global economic environment and widespread global epidemics, the risks of capital outflows and financial assets have increased. This study focuses on the issue of renminbi exchange rate volatility forecasting based on the CARR-MIDAS model, which has important implications for all researchers, investors, policy-makers, and regulators that focus on financial applications in risk measurement, portfolio allocation, and option pricing.

The CARR-MIDAS model is flexible, which allows additional macroeconomic variables such as economic policy uncertainty to be easily incorporated. Thus, future research could be extended to investigate whether macroeconomic information has predictive power for the renminbi exchange rate volatility relying on our CARR-MIDAS approach. [28].

Data Availability

The data on the renminbi exchange rate of the Chinese Yuan (CNY) against the US Dollar (USD) are obtained from the Wind Database of China. All the data are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] T. Bollerslev, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics*, vol. 31, no. 3, pp. 307–327, 1986.

[2] M. Parkinson, "The extreme value method for estimating the variance of the rate of return," *Journal of Business*, vol. 53, no. 1, pp. 61–65, 1980.
[3] S. Alizadeh, M. W. Brandt, and F. X. Diebold, "Range-based estimation of stochastic volatility models," *The Journal of Finance*, vol. 57, no. 3, pp. 1047–1091, 2002.
[4] M. W. Brandt and C. S. Jones, "Volatility forecasting with range-based EGARCH models," *Journal of Business & Economic Statistics*, vol. 24, no. 4, pp. 470–486, 2006.
[5] R. Y. Chou, H. Chou, and N. Liu, "Range volatility: a review of models and empirical studies," in *Handbook of Financial Econometrics and Statistics*, CF. Lee and J. Lee, Eds., Springer, New York, NY, USA, pp. 2029–2050, 2015.
[6] R. Y.-T. Chou, "Forecasting financial volatilities with extreme values: the conditional autoregressive range (CARR) model," *Journal of Money, Credit, and Banking*, vol. 37, no. 3, pp. 561–582, 2005.
[7] C. W. S. Chen, R. Gerlach, and E. M. H. Lin, "Volatility forecasting using threshold heteroskedastic models of the intra-day range," *Computational Statistics & Data Analysis*, vol. 52, no. 6, pp. 2990–3010, 2008.
[8] R. Y. Chou and N. Liu, "The economic value of volatility timing using a range-based volatility model," *Journal of Economic Dynamics and Control*, vol. 34, no. 11, pp. 2288–2301, 2010.
[9] M.-H. Chiang and L.-M. Wang, "Volatility contagion: a range-based volatility approach," *Journal of Econometrics*, vol. 165, no. 2, pp. 175–189, 2011.
[10] E. M. H. Lin, C. W. S. Chen, and R. Gerlach, "Forecasting volatility with asymmetric smooth transition dynamic range models," *International Journal of Forecasting*, vol. 28, no. 2, pp. 384–399, 2012.
[11] C.-Y. Sin, "Using CARRX models to study factors affecting the volatilities of Asian equity markets," *The North American Journal of Economics and Finance*, vol. 26, pp. 552–564, 2013.
[12] R. I. Anderson, Y.-C. Chen, and L.-M. Wang, "A range-based volatility approach to measuring volatility contagion in securitized real estate markets," *Economic Modelling*, vol. 45, pp. 223–235, 2015.
[13] K. H. Ng, S. Peiris, J. S.-K. Chan, D. Allen, and K. H. Ng, "Efficient modelling and forecasting with range based volatility models and its application," *The North American Journal of Economics and Finance*, vol. 42, pp. 448–460, 2017.
[14] H. Xie and X. Wu, "A conditional autoregressive range model with gamma distribution for financial volatility modelling," *Economic Modelling*, vol. 64, pp. 349–356, 2017.
[15] H. Xie and X. Wu, "Range-based volatility forecasting: an extended conditional autoregressive range model," *Journal of Risk*, vol. 21, no. 3, pp. 55–80, 2019.
[16] J. S.-K. Chan, K.-H. Ng, and R. Ragell, "Bayesian return forecasts using realised range and asymmetric CARR model with various distribution assumptions," *International Review of Economics & Finance*, vol. 61, pp. 188–212, 2019.
[17] X. Y. Wu, T. Y. Liu, and H. B. Xie, "Economic policy uncertainty and Chinese stock market volatility: a CARR-MIDAS approach," *Complexity*, vol. 2021, Article ID 4527314, 10 pages, 2021.
[18] R. F. Engle and J. G. Rangel, "The spline-GARCH model for low-frequency volatility and its global macroeconomic causes," *Review of Financial Studies*, vol. 21, no. 3, pp. 1187–1222, 2008.
[19] R. F. Engle, E. Ghysels, and B. Sohn, "Stock market volatility and macroeconomic fundamentals," *The Review of Economics and Statistics*, vol. 95, no. 3, pp. 776–797, 2013.
[20] C. Amado and T. Teräsvirta, "Modelling volatility by variance decomposition," *Journal of Econometrics*, vol. 175, no. 2, pp. 142–153, 2013.
[21] C. Amado and T. Teräsvirta, "Specification and testing of multiplicative time-varying GARCH models with applications," *Econometric Reviews*, vol. 36, no. 4, pp. 421–446, 2017.
[22] F. Wang and E. Ghysels, "Econometric analysis of volatility component models," *Econometric Theory*, vol. 31, no. 2, pp. 362–393, 2015.
[23] C. Conrad and O. Kleen, "Two are better than one: volatility forecasting using multiplicative component GARCH-MIDAS models," *Journal of Applied Econometrics*, vol. 35, no. 1, pp. 19–45, 2020.
[24] C. G. Lamoureux and W. D. Lastrapes, "Persistence in variance, structural change, and the GARCH model," *Journal of Business & Economic Statistics*, vol. 8, no. 2, pp. 225–234, 1990.
[25] A. J. Patton, "Volatility forecast comparison using imperfect volatility proxies," *Journal of Econometrics*, vol. 160, no. 1, pp. 246–256, 2011.
[26] P. R. Hansen, A. Lunde, and J. M. Nason, "The model confidence set," *Econometrica*, vol. 79, no. 2, pp. 453–497, 2011.
[27] F. X. Diebold and R. S. Mariano, "Comparing predictive accuracy," *Journal of Business & Economic Statistics*, vol. 13, no. 3, pp. 253–263, 1995.
[28] S. Degiannakis and A. Livada, "Realized volatility or price range: evidence from a discrete simulation of the continuous time diffusion process," *Economic Modelling*, vol. 30, pp. 212–216, 2013.