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Research Article

Dynamic Interdependence of Systematic Risks in Emerging Markets Economies: A Recursive-Based Frequency-Domain Approach

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We examine the interdependence of systematic risk in twenty emerging market economies. The interdependence structures are performed for subregional and regional categorizations of emerging markets, which have demonstrated financial openness over the years. Hence, the Kalman filter-based wavelet approach is adopted to execute the purpose of this study. The outcome from the contemporaneous correlations demonstrates that the degree of comovements among the equity betas varies. Moreover, from the wavelet multiple cross-correlations, Qatar, Brazil, Indonesia, and Czech Republic led for most timescales. Conversely, the equity betas of United Arab Emirates (Africa and Middle East), Argentina (Americas), China (Asia), and Russia (Europe) exhibit low degrees of integration with other systematic risk returns from each subregion. The low correlations, especially in the short term, of these countries within their respective regions signify less risk transmission and should be included in a portfolio of assets in determining investment risks. Generally, we find significant integration among systematic risks in emerging markets in the long term. We institute that the nature of interdependence in systematic risk has been heterogeneous across time. Accordingly, the equity betas increase with scale for most subregions and the emerging markets as a whole, implying that market interconnections heighten as the investment horizon is prolonged, revealing saturated markets with shocks. It is recommended that prudent liquidity policies are implemented to augment resilience to systematic risks susceptibilities in the long term. The findings present pertinent implications for portfolio diversification, policy decisions, investing risk, and risk management schemes.

1. Introduction

A debatable topic in the literature has been the definition and quantification of risk. Generally, risk is understood as the likelihood of an unfavorable consequence or the dispersion of expected returns and captured as standard deviation [1]. The theoretical rationale for using standard deviation as risk is based on Markowitz [2] who suggested the theory of mean-variance portfolio optimization.

Contrary to the Markowitz's portfolio theory, Sharpe [3] proposed a Capital Asset Pricing Model (CAPM). For a competitive market where all investors are mean-variance optimizers, the CAPM helps predict a direct linear relationship between a security's risk (systematic and unsystematic) and its return. On the other hand, Treynor [4, 5] advocates that the market is compensated for only systematic risk, calculated by beta–unsystematic risk, and can be disregarded by diversification, and thus, not compensated by the market.

Indeed, the cornerstone of modern finance theory is the risk-return trade-off. Most individuals are risk-averse–they require more returns but do not want to assume more risk. Therefore, only if they are rewarded with higher expected returns for bearing the risk can they invest in riskier securities. If the risk-return trade-off [2, 3, 6] is valid, asset portfolios with a high standard deviation should have high expected returns. Contrarily, some studies advocate that there exists inverse relationship between risk and return (see, for example, [7–11]). In the same vein, studies that find a positive relationship between risk and return do not give adequate returns to compensate for a greater risk of high beta stocks [12, 13]. This phenomenon possibly provides an opportunity to reexamine risk minimization strategies/techniques in asset portfolios without necessarily dwelling much on the risk-return trade-off, which is not always guaranteed.

Globally, several studies have explored the performance of stock prices and assets returns [14–16]. In the case of emerging markets, studies have been conducted on CAPM and its international version ICAPM [1, 17, 18]. Nonetheless, the dynamics of systematic risk in the unique context of emerging markets are rarely explored. The rising role of emerging economies in international financial markets needs more focus in order to understand emerging markets, and their extent of comparability.

The growing economic size and technological consequence of emerging markets are among the principal forces determining the global economic and financial market setting. The ongoing capital market liberalization and recuperating market accessibility in emerging markets are triggering rethinking of the future of equity investing. Consequently, capital moves freely within emerging markets to facilitate trade and investment [19]. In this regard, understanding the dynamism of emerging markets, precisely, the speed and path of A shares inclusion, and the configuration and implementation in equity portfolios, especially Chinese market, is central to sound asset allocation decisions [20, 21]. Over the years, China and India have maximized their weight of gross domestic product (GDP) to about 32% and 15%, respectively, relative to other emerging economies fluctuating around 0.4% and 6% [21].

On the other hand, the size of a given stock market within emerging economies is not always linked to the corresponding country economic growth. This is evident since 1994 where market-capitalization weights of Brazil, Malaysia, and Mexico diminished as a percentage of the emerging markets index [21]. Correspondingly, less drastic change in economic weight of these countries was recorded. More distinctively, Korea and Taiwan received higher weights in the MSCI emerging index than the sizes of their economies, China's market-capitalization weight in the index heightened and converged with its share of GDP [21].

The undulating movements of economic and stock performance of emerging economies render their systematic risk worthy of investigating. As a result, investors would have to form reliable portfolios through appropriate assets allocations and portfolio rebalancing to minimize excessive volatility transmission among financial assets. The financial sector borders have expanded, so that individuals can invest in the markets of other countries in different parts of the world as a result of the financial markets integration theory [22]. Global investors' ability to acquire domestic assets, as well as local investors' ability to access international investment opportunities, is vital in enhancing financial markets integration (see, [23, 24]). Investors' risk preference, relative optimism, and information perception, to mention a few, are behavioral features that might impact the preparedness to invest overseas [25, 26]. As a result, the share of GDP from total capital flows within emerging markets has amplified over the years to respond to financial openness [21, 27]. In theory, financial openness fosters international risk-sharing and domestic consumption smoothing [28, 29].

Globalization in the financial system has changed the world economic architecture over few decades [30]. Despite the capital control management during the 2008 global financial crunch where investors were reluctant to invest overseas in risky investment vehicles, economies are recently liberalizing their financial sectors by reducing government regulations and restrictions on capital flows across borders. Capital accounts liberalization is germane to emerging markets, which have demonstrated similar magnitudes of economic and financial development, size and liquidity, and market accessibility to expand and engage aggressively with global markets. Nonetheless, knowledge of capital account liberalization in emerging markets offers many prospects along with challenges for the economic policymakers [30]. Thus, as it encourages assets allocation, it may resort to defect in monetary policy and financial crises. It becomes pertinent to examine the extent of financial openness of the individual emerging economies to facilitate comparisons through comovements and interdependence structures.

According to the Chinn and Ito database, as of 2019, financial openness of emerging countries considered in this study can be arranged as Czech Republic, Greece, Hungary, Qatar, United Arab Emirates, Chile, Saudi Arabia, Russia, Egypt, Malaysia, Thailand, Colombia, Indonesia, Argentina, Turkey, Brazil, China, South Africa, and India. Countries such as Czech Republic, Greece, Hungary, Qatar, and United Arab Emirates have attracted large amounts of capital inflows with success of earlier reforms meant to improve access to international capital markets. On the other hand, Turkey, Brazil, China, South Africa, and India are less opened to capital flows relative to their counterparts emerging economies. In this dynamic system, investors are concerned with the risk of their investments, and their humble desire is to create portfolios that are less volatile but more profitable.

A burgeoning number of empirical studies have exploited various models to measure the risk of financial assets and use them in portfolio selection. These include Dynamic Equicorrelation (DECO) model introduced by Engle and Kelly [31–33], CAPM beta model [1, 17, 34, 35], portfolio optimization for stock market using Value-at-Risk [16], Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model in accordance with CAPM [36], cross-sectional regression using a weighted-least squares approach [37], and GARCH and GAS models through the model confidence set [38, 39].

None of these studies employed Kalman Filter (a recursive property) and multiple wavelet simultaneously to analyze interdependencies among systematic risk in emerging markets in a frequency domain. The traditional approach (CAPM) to beta estimation assumes stationarity; however, several factors influencing the comovements of stocks with the market fluctuate over time [40]. Also, studies that compare Kalman Filter to GARCH models reveal that, due to the issues of forecast errors, Kalman Filter approach is tremendously preferred and considered as the most accurate forecast for equity betas (see, for instance, [41, 42]). Moreover, the wavelet multiple techniques provide the extent of lead/lag relationships and the degree of integration among more than two variables, which are frequency-dependent (see [22, 43, 44]).

The systematic risk of emerging Gulf Cooperation Council (GCC) equity markets was analyzed by Masih, Alzahrani and Al-Titi [45], and was consistent with the theoretical expectation that stock market investors have different time horizons due to different trading strategies, which showed a multiscale pattern in average beta coefficients in all GCC countries. This is because emerging markets in particular are less developed, involve more transaction costs, are highly dependent on individual investors, and are less liquid and prone to infrequent trading. While these findings are defining characteristics of stock markets of emerging economies in general, little is known about the integration of their systematic risks. It is worthy to note that a study that examines the degree of integration among systematic risks of emerging markets is timely.

In this study, we combine Kalman filter and wavelet techniques to analyze the frequency-dependent comovement of systematic risk of twenty emerging stock markets by country and region. This approach is necessary because market participants react to information at diverse timescales, resulting in very noisy market data. To correctly define this issue, the presence of different frequencies would accurately delineate the stock market participants' different investment intrinsic timescales, that is, short, medium, and long term. This is in line with the heterogeneous market hypothesis (HMH) as indicated by Müller et al. [46]. Also, the adaptive market hypothesis (AMH) engineered by Lo [47] suggests that markets evolve due to events and structural changes and adapt, and market efficiency varies in degree at different times. Therefore, frequency-domain analysis would minimize weak signals to maintain the true signals.

Particularly, the contributions of this study to prior studies are threefold. First, we estimate systematic risks returns of twenty emerging markets economies through the Kalman filter approach, which has a recursive property. Second, we investigate the degree of integration among these risks simultaneously to usher a full discussion of the nexus in a frequency domain. Third, to provide a detailed bloc investigation, analyses are performed for subregional and regional categories of emerging markets by the Morgan Stanley Capital International (MSCI). These are needed to enhance knowledge on capital account liberalization in emerging markets to deliver prospects along with challenges for the economic policymakers. Thus, as the patterns of integration among the systematic risk returns induce portfolio diversification and assets allocation strategies for investors, it may resort to defect in monetary policy and financial crises. By this, the paper contributes to literature as the first study to comprehensively examine the structure of systematic risk frequency-domain interdependence among emerging economies.

We found varying degree of contemporaneous correlation among the equity beta pairs for each country based on the regional analysis. It was also clear that lead/lag relationship was scale-dependent. As a result, the equity betas increase with scale for most subregions and the emerging markets as a whole, provided that market interconnections increase as the investment horizon is prolonged revealing saturated markets with shocks.

The rest of the paper is structured as follows. Sections 2 and 3 present the review of related literature and methodology. Results and discussions are presented in Section 4 and concluded in Section 5.

2. Literature Review

The investigation of systematic risk factor models is blatant in finance and economics literature. As noticed from asset pricing, only systematic risk or beta is priced, especially in the equilibrium state, thereby hindering anomalies conditions.

Prior literature on financial risks has welcomed rapid changes over time. The first strand of literature captures dispersion of expected returns through the standard deviation approach. The theoretical rationale for using standard deviation as risk is based on Markowitz's [2] theory of mean-variance portfolio optimization. The theory says that an investor will maximize its expected investment utility either by maximizing the expected return of a portfolio or by minimizing the variance of the portfolio if the returns of investors follow the normal distribution. While both assumptions are controversial, the mean-variance optimization theory of Markowitz has nevertheless provided a fruitful basis for the future growth of modern finance.

Contrary to the Markowitz's portfolio theory, the second strand of literature investigates risks from the standpoint of Sharpe's [3] Capital Asset Pricing Model (CAPM) [34, 35]. For a competitive market where all investors are mean-variance optimizers, the CAPM helps predict a direct linear relationship between a security's risk (systematic and unsystematic) and its return. On the other hand, Treynor [4, 5] advocates that the market is compensated for only systematic risk, is calculated by beta–unsystematic risk, and can be disregarded by diversification, and thus, not compensated by the market. For assets with positive beta, the rule of thumb is to purchase if the Treynor ratio is above the Securities Market Line (SML) and sell if it is below it. It is ideal for all assets to have a Treynor ratio less than or equal to that of the market. However, if, indeed, a positive relationship exists between risk and return, then an asset whose Treynor ratio is bigger than that of the market will probably yield more returns in accord with the systematic risk.

The third component of literature measures risk from the perspective of value at risk in line with the Basel III regulatory framework. This has induced a nascent and fledgling bodies of literature to account for risk in financial time series through a number of GARCH models [39, 48], as well as a combination of GARCH-based models with other models

[49–52]. These studies reveal the extent of volatility transmissions among financial assets either in a time varying or frequency-dependent perspective, or both with the quest of reducing noise from the data.

The fourth strand of literature measures risk based on volatility transmission among financial time series. This is done through either interconnectedness [23, 53], Boateng [54], or information flows among them [24, 55–57]. These studies reveal heterogeneity and adaptive behaviors of financial time series, thereby highlighting the importance of exploiting time and/frequency techniques.

In the context of emerging markets' equity returns, studies have advocated significant linkages [26, 58, 59]. However, little is known about their systematic risk returns linkages. But regarding insights from their equity returns linkages, similar dynamics are expected if the behavior of their equity returns are fully reflected in their systematic risk dynamics revealing some level of markets efficiency. Nonetheless, the heterogeneous nature and adaptive behaviors of financial markets due to the irrational behavior of investors would stimulate diverse outcomes at various investment horizons (short, medium, and long term).

In estimating systematic risk in the unique context of emerging markets, specifically in GCC economies, Masih et al.'s [45] outcome was consistent with the theoretical expectation that stock market investors have different time horizons due to different trading strategies, which showed a multiscale pattern in average beta coefficients in all GCC countries. This is because emerging markets in particular are less developed, involve more transaction costs, are highly dependent on individual investors, are less liquid and prone to infrequent trading. On the other hand, Owusu Junior et al. [60] assert that emerging markets employ prudent liquidity policies to enhance their resilience to systemic risks exposures. Moreover, a study by Arief [49] provides that diffusive and jump risk premia in Southeast Asia emerging markets have heterogeneous influence in other economies, and the outcome differs between high frequency and low frequency samples. However, studies on the integration among systematic risks of emerging markets revealing driving or lagging force are unknown, wherein capital moves freely within emerging markets to facilitate trade and investment [19], and the liberalization strategies instituted by most of their economies. A study on the interdependencies among systematic risks of emerging markets is needed to enhance knowledge on capital account liberalization towards delivering prospects along with challenges for the economic policymakers. It would also offer insights to investors on portfolio diversification and assets allocation strategies.

The novelty of this study is to utilize the Kalman filter technique, which is superior to GARCH in accurately forecasting equity betas [41, 42], in addition to the wavelet multiple techniques, which can describe the phenomenon in diverse investment horizons while reducing noise from the data to effectively assess the emerging markets' systematic risks integration. We utilize twenty emerging economies to capture a broad spectrum of the nexus in terms of subregional and regional integration. The following hypotheses are thus formulated with insights from prior theoretical and empirical outcomes in the context of emerging economies:

(a) There are strong interdependencies among systematic risks of emerging economies.

(b) The systematic risks interdependencies are scale-dependent.

3. Methodology

The analytical procedure is structured such that time-varying betas of the stock markets included in the study are obtained using the standard ICAPM based on the Kalman filter estimation. The Kalman filter is utilized in this study to estimate daily equity betas, due to its recursive property. This is followed by the wavelet multiple technique specifically, bivariate contemporary correlations (BCC), wavelet multiple correlations (WMC), and wavelet multiple cross-correlations (WMCC) as well defined by Gençay et al. [61] and Percival and Walden [62]. The wavelet multiple is specifically employed in this study to assess the dynamic interdependencies among the emerging markets.

3.1. The Kalman Filter Model. In the engineering literature of the 1960s, control engineers developed a significant concept called "state space" to describe structures that fluctuate over time [63]. Measurement and transition equations, which simultaneously direct a system's structure and dynamics, are represented in the general form of a state space model. An observation at time t in a linear combination of a number of variables in a state space model, referred to as state variables, makes up the state vector at time t. We designate the number of state variables by z and the $(z \times 1)$ vector by γ_t. The observation (measurement) equation can be presented as

$$Y_t = H_t \gamma_t + \eta_t, \quad (1)$$

where Y_t is the observation vector at time t; $\gamma_t = (z \times 1)$ process state vector at time t; $H_t = (z \times z)$ observation matrix; $\eta_t = (z \times 1)$ observation error, which is generally assumed to be Gaussian normal with zero mean, $\eta_t \sim N(0, \sigma_V^2)$.

The state variables may be specified as a minimum set of information conditioned on the past and present values, but the future state of time series is dependent only upon the present state. This is in line with the Markov property that the latest value of variables is appropriate to make forecasts other than past values. This is synonymous to the Random Walk Theory in the sense that stock prices follow a random movement when markets are efficient, and therefore, historical information is impossible to predict future stock prices.

Sharpe [3] and Lintner [64] advocate that Capital Asset Pricing Model (CAPM) defines the expected market rate of return of a specific asset in relation to the expected risk. The Sharpe-Lintner version of CAPM proposes a steady linear relationship between the expected excess return and undiversifiable risk (systematic risk) of holding financial asset. Beta has been one of the most common and accepted tools used by financial economists and market experts in order to manage and assess risk. The standard CAPM postulates that

$$er_{i,t} = \alpha_t + \beta_{i,t}\left(r_{p,t}\right) + \varepsilon_i, \quad (2)$$

where $er_{i,t}$ denotes excess returns on individual stock i; $r_{p,t}$ signifies risk premium; $\beta_{i,t}$ shows beta of individual stock; ε_i is the disturbance term, which is normally and independently distributed with constant variance σ_ε^2. But–$er_{i,t} = re$–rf; and $r_{p,t} = rm - rf$; re = return on individual stock, rf = risk free rate; α_t and $\beta_{i,t}$ denote time-varying parameters; rm = return on the market.

To execute a time-varying structure of the ICAPM beta, we follow Faff, Hillier, and Hillier [65]; and Choudhry and Wu [41] by employing a state space model to incorporate unobserved variables with observable model and estimate them. The domestic CAPM can be extended to international settings and write a single factor international CAPM (ICAPM) as

$$ER_{i,t} = a_t + \beta_{i,t}\left(R_{p,t}\right) + \mu_{i,t}, \quad (3)$$

where $ER_{i,t}$ and $R_{p,t}$ are excess returns for i^{th} market portfolio and market risk premium, a_t means time-varying average return on market portfolio, and $\beta_{i,t}$ denotes time-varying beta returns of i^{th} market portfolio $\mu_{i,t}$ = Disturbance term. But; $ER_{i,t} = Re$–Rf, and $r_{p,t} = Rm - Rf$; and; Re = return on the market portfolio, Rf = risk free rate and Rm = return on the world portfolio.

The time-varying beta structure is clearly modelled within the Kalman filter framework to follow any stochastic process. The series of conditional intercepts and the parameters for the ICAPM are generated based on an initial set of priors due to the recursive nature of the Kalman filter. Equation (3) signifies the observation equation of the state space model, inferred from equation (1). This paper uses the type of random walk that offers the best characterization of the time-varying beta compared to the AR(1) and random coefficient types of transition equation in order not to encounter the difficulty of return series convergence. The transition equation can thus be presented as

$$\beta_{i,t}^{\text{Kalman}} = \beta_{i,t-1}^{\text{Kalman}} + \omega_t, \omega_t \sim N(0, \varnothing) \quad (4)$$

The state space model can be obtained from equations (3) and (4). Moreover, to forecast the future value, we express the prior conditionals necessary for using the Kalman filter as

$$\beta_0^{\text{Kalman}} \sim N\left(\beta_0^{\text{Kalman}}, P_0\right), \quad (5)$$

With the aid of the prior condition, we estimate the entire series of conditional beta based on the Kalman filter recursive property. The choice of Kalman Filter over its competitors such as GARCH is motivated by its superiority in accuracy in forecasting equity betas (see, for instance, [41, 42]).

3.2. Wavelet Multiple. Let $X_t = x_{1t}, x_{2t}, \ldots, x_{nt}$ follow a multivariate stochastic process, and let $W_{jt} = w_{1jt}, w_{2jt}, \ldots, w_{njt}$ be a resultant scale λ_j. MODWT is used to estimate wavelet coefficients. Fernández-Macho [66] postulated that the WMC is known as $\Omega X(\lambda_j)$ which is a customary of multiscale coherence estimated from X_t that is shown in equation (6). The coefficient of determination (R^2) square roots from the regression fashioned by the direct grouping of $w_{ijt}, i = 1, 2, \ldots, n$ variables that make R^2 maximize are estimated in every wavelet scale λ_j. Prior research has shown that supplementary regressions are unnecessary since R^2 fits the conditions for the regression of a variable z_i by a set of predictors $\{z_k, k \neq i\}$ that can be represented as $R_i^2 = 1-\rho^{-ii}$, where ρ^{ii} is the i^{th} diagonal portion of the inverse of the complete correlation matrix P. Therefore, WMC is shown in the following equation:

$$\Omega X(\lambda j) = \left(1 - \frac{1}{\max \operatorname{diag} P_j^{-1}}\right)^{1/2}, \quad (6)$$

where Pj is an $(n \times n)$ correlation matrix in W_{jt}.

Fitted values of z_i from a theory of regression are $\widehat{z}_t$; therefore, the WMc is shown in the following equation:

$$\Omega X(\lambda j) = \operatorname{Corr}\left(w_{ijt}, \widehat{w}_{ijt}\right) = \frac{\operatorname{Cov}\left(w_{ijt}, \widehat{w}_{ijt}\right)}{\left(\operatorname{Var}\left(w_{ijt}\right)\operatorname{Var}\left(\widehat{w}_{ijt}\right)\right)^{1/2}}, \quad (7)$$

where w_{ij} is used to capitalize on $\Omega X(\lambda_j)$ and $\widehat{w}_{ijt}$ represents the fitted values in the regression of w_{ij} on the outstanding wavelet coefficients at scale λ_j.

Therefore, WMCC is known by permitting a lag τ amid fitted values and observed at individual scale λ_j

$$\Omega X, \tau\left(\lambda_j\right) = \operatorname{Corr}\left(w_{ijt}, \widehat{w}_{ijt+\tau}\right) = \frac{\operatorname{Cov}\left(w_{ijt}, \ddot{\widehat{w}}_{ijt+\tau}\right)}{\operatorname{Var}\left(w_{ijt}\right)\operatorname{Var}\left(\widehat{w}_{ijt+\tau}\right)}, \quad (8)$$

where for $n = 2$, WMCC and WMC unite with the cross-correlation and standard wavelet correlation.

To calculate WMCC and WMC, let $X = \{X_1, X_2, \ldots, X_T\}$ be the recognition of the multivariate stochastic process X_t for $t = 1, 2, \ldots, T$. MODWT of order J is linked to individual univariate time series $\{X_{1i}, \ldots, X_{1T}\}$, for $i = 1, 2, \ldots, n$, the Jlength $- T$ vectors of coefficients of MODWT $\widetilde{W}_j = \left\{\widetilde{W}_{j1}, \widetilde{W}_{j1}, \ldots, W\widetilde{W}_{j,T-1}\right\}$, for $j = 0, 1, \ldots, J$ is obtained.

In equation (10), a nonlinear function of all $n(n-1)/2$ wavelet correlations of scale λ_j and a steady estimator of wavelet correlation from the MODWT are shown in

$$\begin{aligned}\widetilde{\Omega} X\left(\lambda_j\right) &= \left(1 - \frac{1}{\operatorname{maxdiag}\widetilde{P}_j^{-1}}\right)^{1/2} = \operatorname{Corr}\left(\widetilde{w}_{ijt}, \widehat{\widetilde{w}}_{ijt}\right) \\ &= \frac{\operatorname{Cov}\left(\widetilde{w}_{ijt}, \widehat{\widetilde{w}}_{ijt}\right)}{\left(\operatorname{Var}\left(\widetilde{w}_{ijt}\right)\operatorname{Var}\left(\widehat{\widetilde{w}}_{ijt}\right)\right)^{1/2}},\end{aligned} \quad (9)$$

where $\widetilde{w}_{ij}$: the regression of the equivalent set of regressors $\left\{\widetilde{w}_{kj}, k \neq i\right\}$ optimizing the R^2, $\widehat{\widetilde{w}}_{ij}$ denotes meeting the requirements fitted values, and $L_j = (L-1)(2^j - 1)$ shows the number of wavelet coefficients impacted by the boundary constraints associated with a length wavelet filter L and scale λ_j but $\widetilde{T} = T - L_j + 1$ shows the number of wavelet coefficients that are not influenced by boundary conditions.

Similarly, a reliable equation for the WMCC can be estimated as

$$\widetilde{\Omega}X, \tau(\lambda_j) = \mathrm{Corr}\left(\widetilde{w}_{ijt}, \widetilde{\widetilde{w}}_{ijt+\tau}\right) = \frac{\mathrm{Cov}\left(\widetilde{w}_{ijt}, \widetilde{\widetilde{w}}_{ijt+\tau}\right)}{\left(\mathrm{Var}\left(\widetilde{w}_{ijt}\right)\mathrm{Var}\left(\widetilde{\widetilde{w}}_{ijt+\tau}\right)\right)^{1/2}}. \tag{10}$$

Fernández-Macho [66] applies the transformation arctan $h\,(r)$, where arctan $h\,(.)$ is the inverse hyperbolic tangent function for simplicity's sake, to estimate the confidence interval (CI) of WMC [43]. The confidence interval was estimated from the same thought of the realization of X in the calculation of WMC and WMCC and hence for $\widetilde{\Omega}X(\lambda_j)$ in equation (9), the $\widetilde{z}_j \sim F\aleph(z_j, (T/2^j - 3)^{-1})$, where $z_j = \mathrm{arctan}h(\Omega X(\lambda_j)), \widetilde{z}_j = \mathrm{arctan}h(\widetilde{\Omega}X(\lambda_j))$, and $F\aleph$ symbolize the folded normal distribution. Thus, an estimate $(1-\alpha)$ CI is represented by

$$\mathrm{CI}(1-\alpha)\left(\Omega X\left(\lambda_j\right)\right) = \tanh\left[\widetilde{z}_j - \frac{C_2}{\left(\left(T/2^j\right)-3\right)^{1/2}}; \widetilde{z}_j + \frac{C_1}{\left(\left(T/2^j\right)-3\right)^{1/2}}\right], \tag{11}$$

where the $F\aleph$ critical values C_1, C_2 are: $\Omega(C_1) + \Omega(C_1 - 2z^0) = 1 - \alpha/2$ and $\Omega(C_2) + \Omega(C_1 - 2z^0) = 2 - \alpha/2$ with $\Omega(.)$ as the standard normal distribution function and $\tanh(z^0) = \Omega_X^0(\lambda)$ as the value of a WMC calculated under the null hypothesis of no connection.

3.3. Data Sources and Description. The data used for the study consists of twenty emerging markets' daily stock returns as classified by the Morgan Stanley Capital International (MSCI), Global stock index returns and risk free rate proxied by the US 91-day treasury bill rate. The data span from 23rd August 2010 to 3rd November 2020, making up a total of 833 observations after the data were merged in R statistical software to have common date for equitable comparison. The suggested period was chosen to cover the US-China trade tension, Brexit, and the COVID-19 pandemic. The countries were selected based on consistent and reliable data availability for the chosen periods, yet it contains most of the essential markets of the emerging economies. Daily data was selected over monthly/yearly series because daily data uses better-off information to compensate for the rapid fluctuations of financial information [67]. The data on stock market indices and the US Treasury bill were obtained from EquityRT database.

We consider the US Treasury bill because its bonds are generally believed to be of the highest credit quality, being backed by the full faith and credit of the U.S. government, and interest rates of most developing and emerging economies are procyclical to those of the US (see, [68, 69]). Also, due to openness of capital accounts in most emerging economies, portfolio equity inflows in more open nations are largely susceptible to fluctuations in the US treasury rates than domestic returns [70]. Moreover, as posited by Nguyen, Nguyen, and Schinckus [71], sensitivity of emerging

Table 1: Emerging Market Economies classification by region.

Africa & Middle East	Americas	Asia	Europe
Egypt	Argentina	China	Czech Republic
South Africa	Brazil	India	Greece
Qatar	Colombia	Indonesia	Hungary
Saudi Arabia	Chile	Malaysia	Russia
Turkey		Taiwan	
United Arab Emirates (UAE)		Thailand	

countries to the US provides reasonable stable numéraire in investors' minds. We do not control for any other macroeconomic condition in the analysis because fluctuations in the macro variables would enable us to effectively examine the systematic risk nexus in the emerging economies. The daily equity betas were obtained with the help of the Kalman Filter, due to its recursive property. The continuous compounded returns of the indices with $P_{i,t}$ as the price index of market i at time t, $R_{i,t}$, are calculated as follows: $R_{i,t} = \mathrm{Ln}(P_t/P_{t-1})$.

According to the MSCI [21], emerging markets currently consist of 27 emerging-market economies. However, due to consistent data availability for the chosen period, which covers most important economic events, the analysis is conducted on 20 countries. The remaining 7 stock markets returns were specifically expunged from the analysis due to limited number of data for the selected period. The sample of 20 is representative for the analysis because it covers the majority of countries within the regional categorization by the MSCI. Notwithstanding, these 20 emerging economies are touted to be speedily expanding and engaging aggressively with global markets. With the increase in financial markets integration, these economies are considered to depict similar dimensions of economic and financial development, size and liquidity, and market accessibility with time regarding several regional classifications. Moreover, these emerging markets are seen to be risky investment, owing to excessive political risks and currency exchange volatilities with high tendency to aggravate systematic risks. Consequently, investors of these markets should highly expect volatile returns although the potential gains from these emerging markets are sizeable, and highly comparable to their potential losses. It becomes well intentioned to focus the analysis based on subregional and entire regional (emerging markets) classifications to quantify the extent of interdependencies among the 20 emerging economies. The world emerging markets are categorized into three regions, that is, Americas; Asia; and Europe, Middle East and Africa (EMEA). To have an in-depth analysis of both regional and global interdependencies, we further categorize the emerging markets as shown in Table 1.

3.4. Descriptive Statistics. Figure 1 shows the graphical representation for equity beta indices and returns series of twenty countries from emerging market economies based on regions. An informal stationary test was done by analyzing

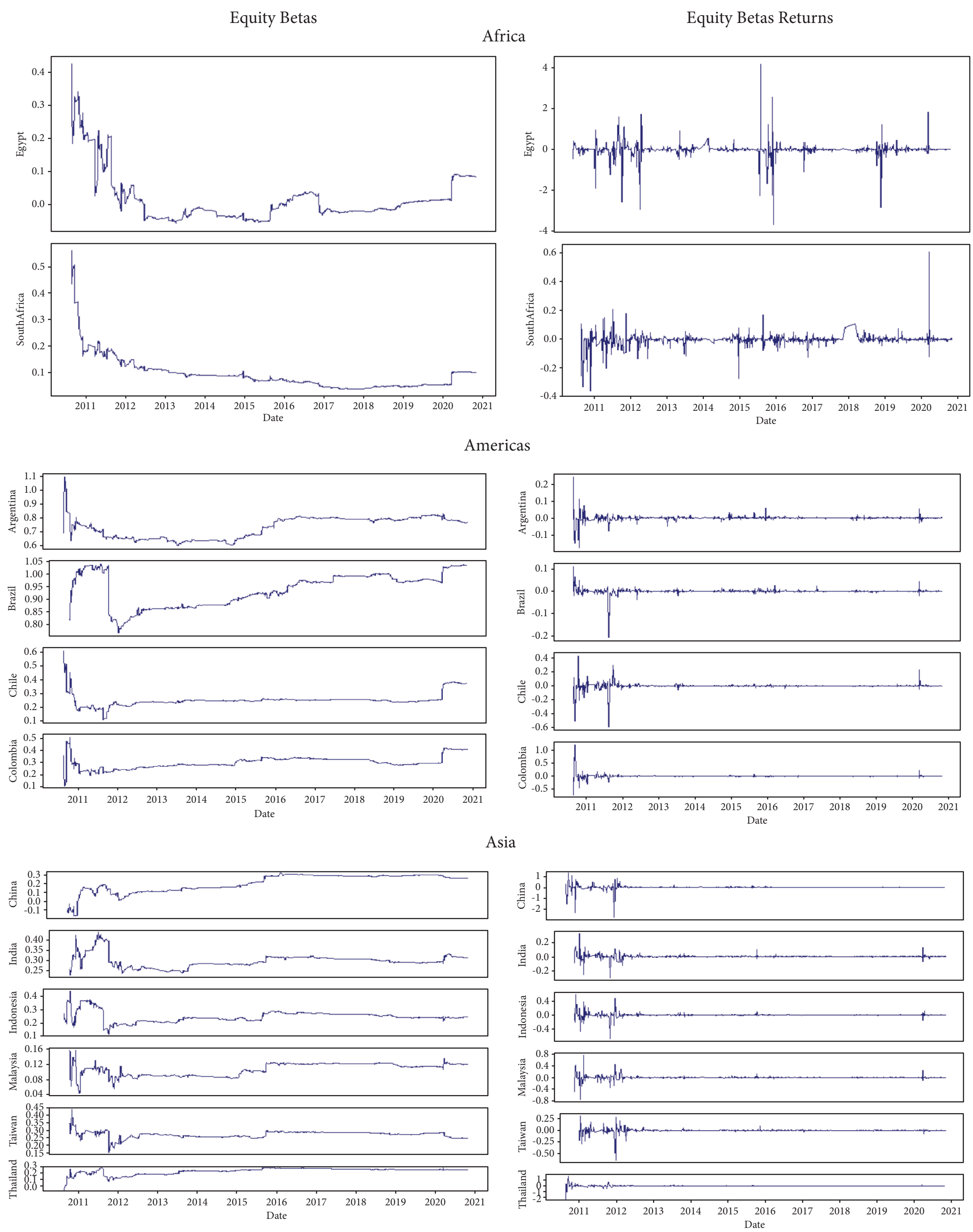

Figure 1: Continued.

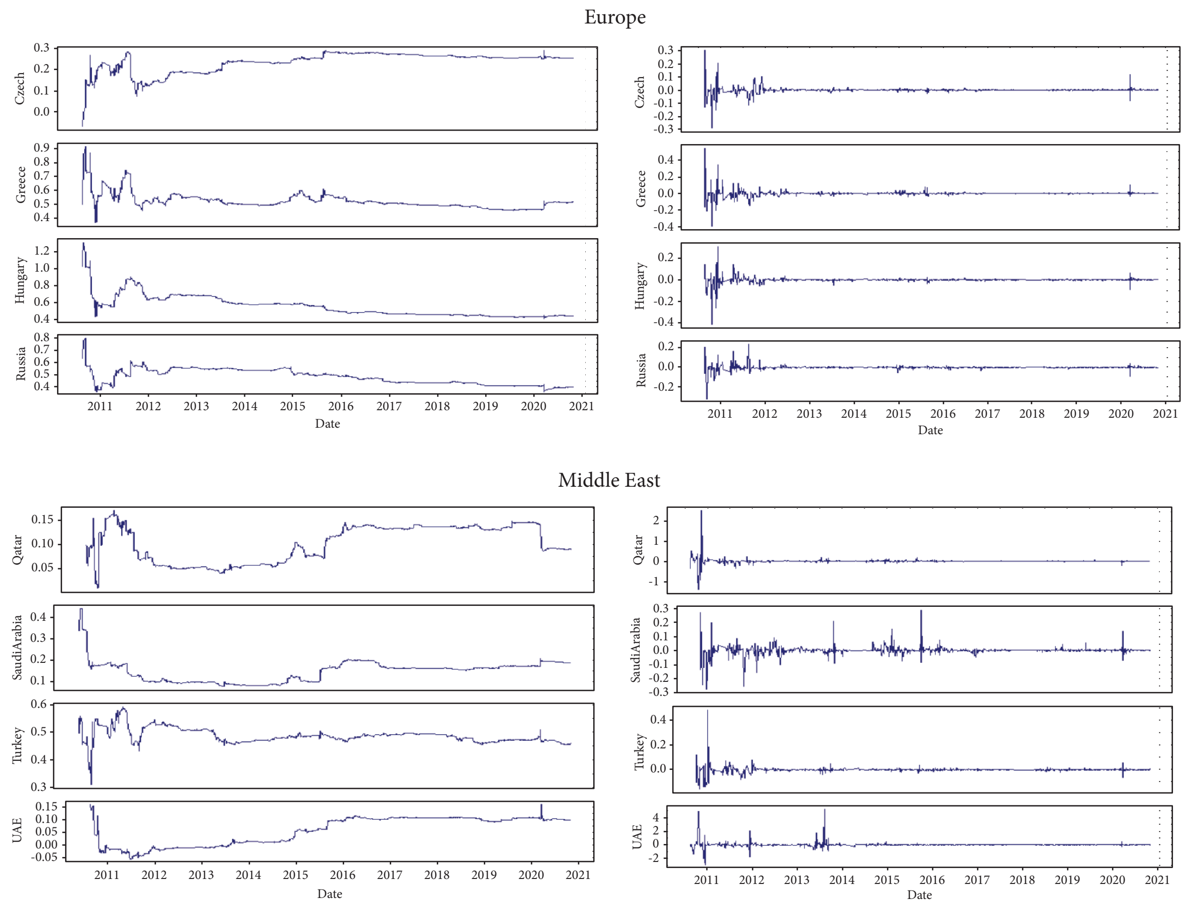

Figure 1: Graphical representation of equity betas of time series data.

the trend of the indices and returns used in the study. Most beta indices trend upwards for some time after the spike, which suggest that these series are nonstationary. This depicts that some countries within emerging market economies after the recent Global Financial Crisis have been experiencing increasing betas, except for Africa and Europe. Again, the returns tend to follow the same pattern. They become stationary after the first difference of all the variables as they revert around zero, as presented in Figure 1.

The following examines the equity beta indices extensively for each region within the emerging market economies to assess its fluctuations over the period of the study for careful comparison and policy decisions. A quick glance at the initial stage of the equity beta indices (plots) indicates a spike, specifically a large downward movement of betas for a short period of time. The outcome may not seem surprising since the period considered for the study takes into account the recovery from the 2008 Global Financial Crisis. Most equity beta indices trend upwards for some time after the downward spike. This depicts that some emerging market economies after the recent Global Financial Crisis have been experiencing increasing betas. At the latter part of the graph (approximately beyond 2016) for most countries, there seems to be an upward trending of betas. This may be due to shocks from the US-China trade tension, the 2020 Russia-Saudi Arabia oil price war, etc. and may require further analysis by researchers to ascertain the extent to which the presence of uncertainties is likely to influence systematic risk. Specifically, around 2020, there seem to be rising systematic risks for most emerging economies, and this could be due to adverse impacts from the COVID-19 pandemic shocks on global markets.

Moreover, considering countries whose beta trends are largely deviating from the rest within their respective regions including Brazil and Argentina from Americas and Turkey from the Middle East, the equity beta of China is showing a spike at the early stage of the trend, which suggests high inconsistency within the Asian region. Overall, the betas of Brazil seem to deviate graphically from the rest of the countries between 0.8 and 1.0 frequencies. This necessitates the stock market of Brazil to proceed with caution in order not to experience more volatile stock prices than the market in the near future. Notwithstanding, almost all the countries have a less than 1 beta, which is less than that of the market, demonstrating a defensive stock. Policy makers, governments, and international unions across the globe should fine-tune their economic policies to restore these betas to an appropriate level required by investors.

Table 2 depicts the descriptive statistics of the equity beta indices of the twenty Emerging Market Economies considered for this study. All betas had positive means with those of Egypt approaching zero. Moreover, the betas are less than 1, which signifies that the securities' prices are less volatile than the market. However, the beta of Brazil is noticed in approach 1, which requires immediate attention by existing and potential investors. As a result, investors of Brazilian stocks will demand higher equity premium to be compensated for taking on a higher risk of equity investing; nonetheless, the higher equity premium may not always be assured. This confirms the study of Araújo et al. [72] where the equity premium has been higher in Brazil, but the much higher Brazilian uncertainty to risk (volatility) discourages heavier investments in stocks. Again, most of the betas were positively skewed, for instance, African and European countries considered in this study. On the other hand, stock markets with the negatively skewed betas should proceed with caution since there is a potential for repeated greater losses due to the presence of increasing beta values. The equity beta of China is highly dispersed within the Asian region. This outcome may require further analysis to indicate the extent to which China can be considered as an open large country, and likely to receive shocks from trading with other countries. The same can also be said about Hungary in Europe. It could further be observed that all the dataset is not normally distributed, which supports the use of frequency-dependent techniques, consistent with the behavior of financial time series.

Table 2: Descriptive statistics of equity beta indices.

Regions/countries	Mean	Std. dev.	Skewness	Kurtosis	Jarque-Bera
Africa					
Egypt	0.0146	0.0700	2.3699	9.8499	2408.3320***
South Africa	0.0858	0.0576	3.7026	23.8354	16970.6500***
Americas					
Argentina	0.7396	0.0730	−0.2937	2.3008	28.9454***
Brazil	0.9451	0.0620	−0.5407	2.4394	51.4980***
Chile	0.2562	0.0477	2.6434	15.4249	6328.3130***
Colombia	0.3070	0.0463	0.5792	4.7176	148.9597***
Asia					
China	0.2175	0.0962	−1.3803	5.1310	422.1302***
India	0.2981	0.0309	1.2916	7.0186	792.1197***
Indonesia	0.2486	0.0354	0.7719	5.8252	359.7646***
Malaysia	0.1091	0.0155	−0.7515	3.3042	81.6212***
Taiwan	0.2723	0.0192	−0.0079	12.2954	2998.9770***
Thailand	0.2394	0.0454	−2.2878	10.7940	2835.0460***
Europe					
Czech	0.4796	0.0908	1.4657	7.1039	882.7948***
Greece	0.5211	0.0515	2.5046	14.8178	5718.3300***
Hungary	0.5386	0.1185	1.8816	8.5420	1557.5630***
Russia	0.4770	0.0616	0.5276	3.4123	44.5436***
Middle East					
Qatar	0.1043	0.0363	−0.4772	1.7422	86.5308***
Saudi Arabia	0.1483	0.0457	1.0694	8.7787	1317.7890***
Turkey	0.4845	0.0265	0.0719	10.1953	1797.6560***
UAE	0.0636	0.0528	−0.6443	1.8087	106.8958***

4. Results

4.1. Comovement of Systematic Risk. The following section examines the regional and overall systematic risk comovement of emerging market economies. The regional analysis for the purpose of this study will be categorized as Africa and Middle East, Americas, Asia, and Europe. This categorization is shown to ascertain a substantial understanding of the dynamic interdependence of systematic risk in emerging markets, and to also draw inferences for economic policy decisions for each region. The overall analysis will enable the authors to clearly determine the countries that drive the comovement at various frequencies. The pictured plot incorporates the six scales into one plot to facilitate easy interpretation.

The study presents numerous wavelet cross correlations for various time scales with 15 days for the visualized plot of the wavelet (approximately half month). The classical plot helps us decide the multiple wavelet cross correlation graph's symmetry, while the visualized plot provides multiple cross correlations of the wavelet's strength. Again, the vertical long-dashed lines allow readers to accurately evaluate the time lag at which the strongest values of wavelet correlation are localized. Localizations at positive lag denote lagging variable and negative lag denote leading variable at the respective scales. The confidence interval spanning zero can also be easily recognized. At the zero lag of localization (dashed) lines, there is no lead or lag. Sections within the confidence interval spanning zero are shown in white. Localization implies the maximum values in the linear combination of all variables (equity betas) at the wavelet scales, which are indicated by dashed lines within the dotted lines (at all lags). A variable listed on a scale indicates the variable with the potential to lead or lag all the other variables. It implies that, at that scale, it has the maximum value in the linear combination of all the variables (equity betas) at the respective scales. When a dashed line accompanies a listed variable in the heatmap, then it becomes an actual lead (negative lag) or lag (positive lag) unless the dashed line is on the zero lag, which implies neither lead nor lag. Accordingly, the economic implication of the wavelet multiple cross-correlation (WMCC) is that it indicates the degree of interdependence between the variables and determines the most influential equity beta from a particular country at a specified wavelet scale to act as either a leading (first mover to respond to shocks) or lagging (the last variable to respond to shocks after the remaining variables) variable. To conclude, on the right side of each wavelet scale, the country that maximizes the multiple cross-correlations against a linear combination of the remaining variables is clearly presented. For the wavelet correlation, the wavelet coefficients are located within the 95 percent confidence interval.

The meaning of the scales in the care of data frequency of 5 days per week, lj, $j = 1, \ldots, s6$, of the wavelet factors is connected to times of, respectively, "2–4 days (intraweek scales), 4–8 days (weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (monthly to quarterly scale), and 64–128 days (quarterly to biannual scale)" for scales 1–32, respectively [43, 44, 73]. These scales are represented in the y-axis from Figures 2–15.

4.1.1. Systematic Risk Comovement in the African and Middle East Regions. At 6 wavelet scales, the bivariate contemporary correlations are considered. The codes for the variables are Egypt (C1), South Africa (C2), Qatar (C3), Saudi Arabia (C4), Turkey (C5), and UAE (C6). For calculating wavelet correlation coefficients, the horizontal axis displays the combinations. If we switch from left to right, the dynamic interdependence between the systematic risks of Africa and Middle East becomes weaker. On the vertical axis, the wavelet scales reflect time periods.

In Figure 2, we present the wavelet correlation matrix for the systematic risk of Africa and Middle East across the six scales. We find a mix of direct and inverse relationships among the pairs. Qatar and Saudi Arabia demonstrated the maximum degrees of comovement with coefficients fluctuating over 0.29 to 0.95 at diverse time scales (scales 1–32) averaging 0.51, indicating the presence of extreme correlational values. Nonetheless, there are relatively lower levels of correlation between the systematic risk of United Arab Emirates and the rest of the countries. The result is similar to the study of Joseph and Fernandez [74], where UAE stock markets returns exhibited different behavior from other GCC stock markets returns. The study, moreover, confirms their suggestion for further research, where, in terms of risk, the stock markets of UAE would embellish and considered a defensive stock, which can be relied upon to form reliable portfolios.

Figure 3 represents the wavelet multiple correlation for the systematic risk nexus of Africa and Middle East. It could be argued that the nature of the correlation is far from identical both along time and across frequencies. From Figure 3, multiple correlations concentrate at large (above 0.7) at all-time scales except at scale 4, representing a monthly scale. It begins with a correlation coefficient of about 0.72 at intraweek scale, attaining minimum at weekly scale (0.42). The variation in the correlation continues until it reaches a peak of about 0.98 at quarterly to biannual scale. Overall, the systematic risk dynamics of Africa and Middle depict less connectedness in the medium term but converge in the long term at scale 32.

The wavelet multiple cross correlation coefficients are presented in Figure 4 and Table 3 depicting six wavelet scales. We find that the systematic risk of Qatar has the potential to lead or lag for most of the time scales and can maximize the multiple cross-correlations from a linear combination of the remaining systematic risks from monthly to biannual scale representing medium- and long-run comovement. The systematic risk of Turkey has the potential to lead or lag (at time 0) specifically at intraweek and weekly scales, Saudi Arabia has the potential to lead or lag at fortnight to monthly scales (at time 0), and Qatar leads (at times 0 and −1) at monthly to quarterly scale. The failure for the systematic risk of Egypt, South Africa, and United Arab Emirates to drive the relationship is due to less integration of their systematic risk returns within the Africa and Middle East regions. This can also be ascribed to the advancement of their stock markets, thereby minimizing their degree of dependence on the rest of the markets. Also, the systematic risk nexus within these countries stock markets was found to be low as compared to the rest. Empirically, in terms of stock returns driving tendency, the stock returns of Egypt and South Africa have the potential to lead most of the nexus among the developed stock market returns of crude oil producing countries in Africa. Likewise, Joseph and Fernandez [74] found out that United Arab Emirate's stock markets are considered to be developed and able to thrive even in times of economic downturn. Categorically, the stock markets of Egypt, South Africa, and United Arab Emirate are well developed and well integrated into emerging markets. In addition, the less interdependencies among the equity beta returns of some countries are beneficial to conservative investors since they offer diversification, hedge, and safe haven benefits.

4.1.2. Systematic Risk Comovement in the Americas Region. From Figure 5, we present the wavelet correlation matrix for systematic risk of Americas across the six scales. We find a mix of direct and inverse relationships among the pairs. Chile and Columbia demonstrated the maximum degrees of comovement with coefficients fluctuating over 0.03 to 0.74 at diverse time scales indicating the presence of extreme correlational values. The outcome of the study proves that the systematic risk of Argentina demonstrated relatively lower levels of correlation with the remaining systematic risk returns. This can be confirmed from the descriptive statistics of the study, where Argentina demonstrated extreme segmentation from the remaining countries within Americas. Moreover, there exists a high degree of negative comovements between the systematic risks of Brazil and Argentina but only in the long run. Contrarily, studies that evaluate the comovement between Argentina and Colombia stock markets find a significant relationship, but the comovements between Brazil, Chile, and Colombia are statistically significant [75]. This transcends to their systematic risks interdependence dynamics to establish that, generally, there exist high interdependencies between the systematic risks of Brazil, Chile, and Colombia, but less associated with Argentina. The low correlations between the systematic risk of Argentina and the remaining economies suggest that investors would minimize their investing risk when they include stocks of Argentina in a portfolio.

Figure 6 represents the wavelet multiple correlation for the systematic risk nexus of Americas. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. It begins with a correlation coefficient of about 0.41 at intraweek scale and attains maximum at fortnight scale (0.81). The variation in the correlation continues until it reaches about 0.79 at biannual to annual scale.

The wavelet multiple cross-correlation coefficients are presented in Table 4 depicting six wavelet scales. We find that systematic risk of Brazil has the potential to lead for most of the time scales and can maximize multiple cross-correlations

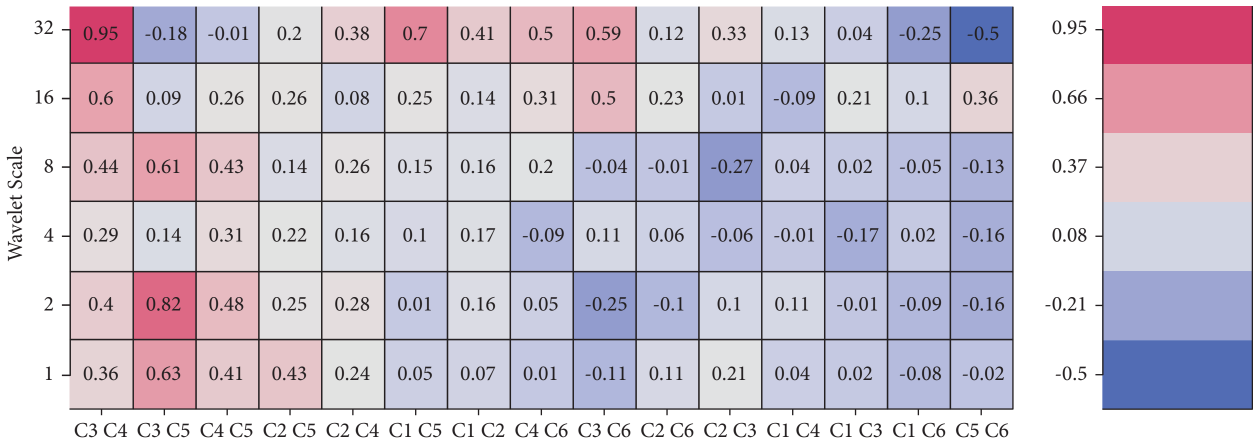

Figure 2: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are Egypt (C1), South Africa (C2), Qatar (C3), Saudi Arabia (C4), Turkey (C5), and UAE (C6).

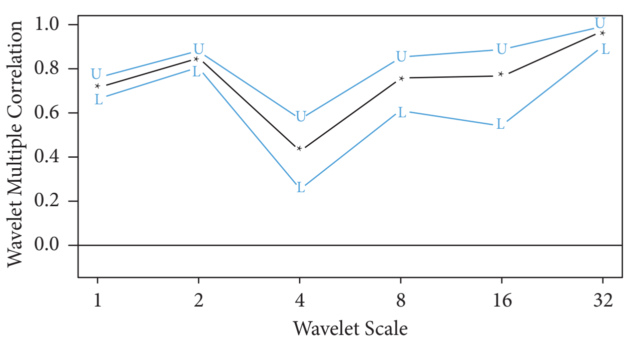

Figure 3: Wavelet multiple correlation between systematic risk of Africa and Middle East (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

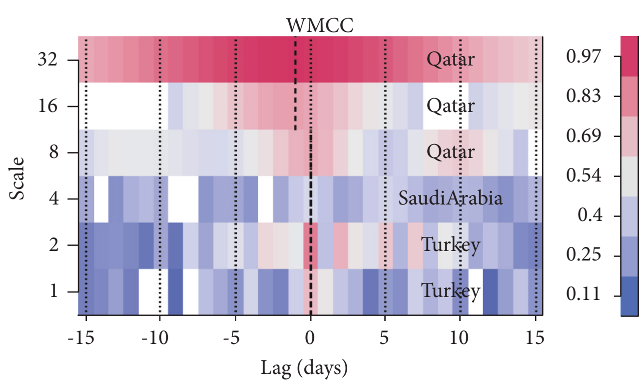

Figure 4: Wavelet multiple cross correlation between systematic risk of Africa and Middle East (18/08/2010–03/11/2020).

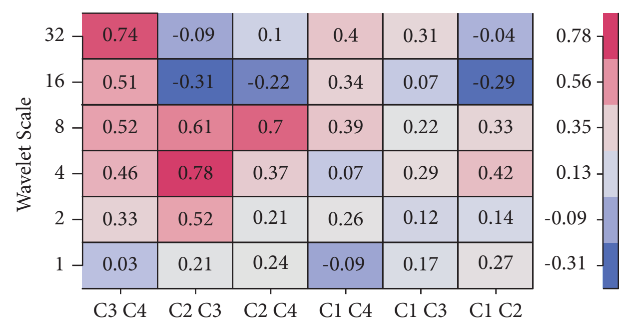

Figure 5: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are Argentina (C1), Brazil (C2), Chile (C3), and Columbia (C4).

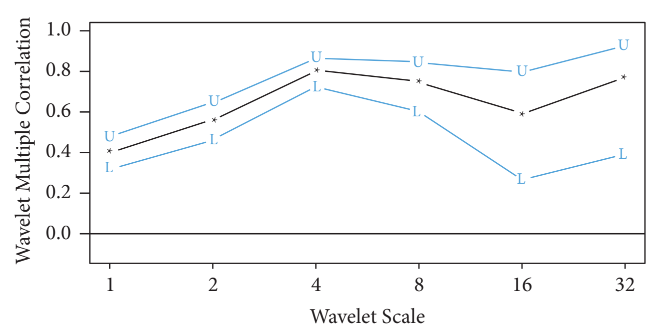

Figure 6: Wavelet multiple correlation between systematic risk of Americas (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

from a linear perspective of combination of the remaining systematic risks. The systematic risk of Brazil leads (at time −1 day) specifically at intraweek scale. Chile and Brazil have the potential to lead or lag (at time 0 day) at weekly and fortnightly scales, respectively. This is followed by Brazil again, which leads at monthly scale (at time −7 days). On the other hand, Colombia has the potential to lead or lag at monthly to quarterly scale (at time 0 day) but lags quarterly to biannual scale (at time 7 days). This implies that innovations as well as global uncertainties in Brazil, Chile, and Colombia have the potential to drive the systematic risk interdependence in Americas rendering Argentina to be less integrated.

4.1.3. Systematic Risk Comovement in the Asian Region. In Figure 8, we present the wavelet correlation matrix for systematic risk of Asia across the six scales. Surprisingly, we

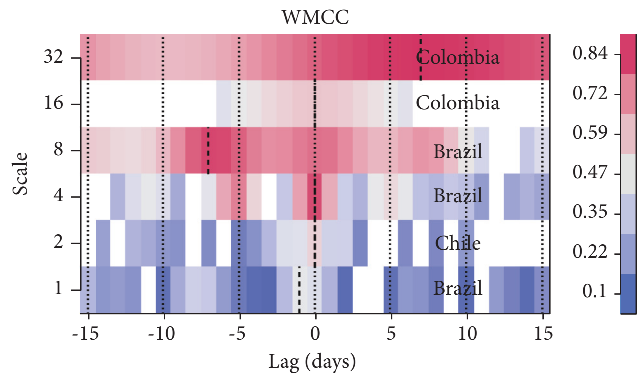

Figure 7: Wavelet multiple cross correlation between systematic risk of Americas (18/08/2010–03/11/2020).

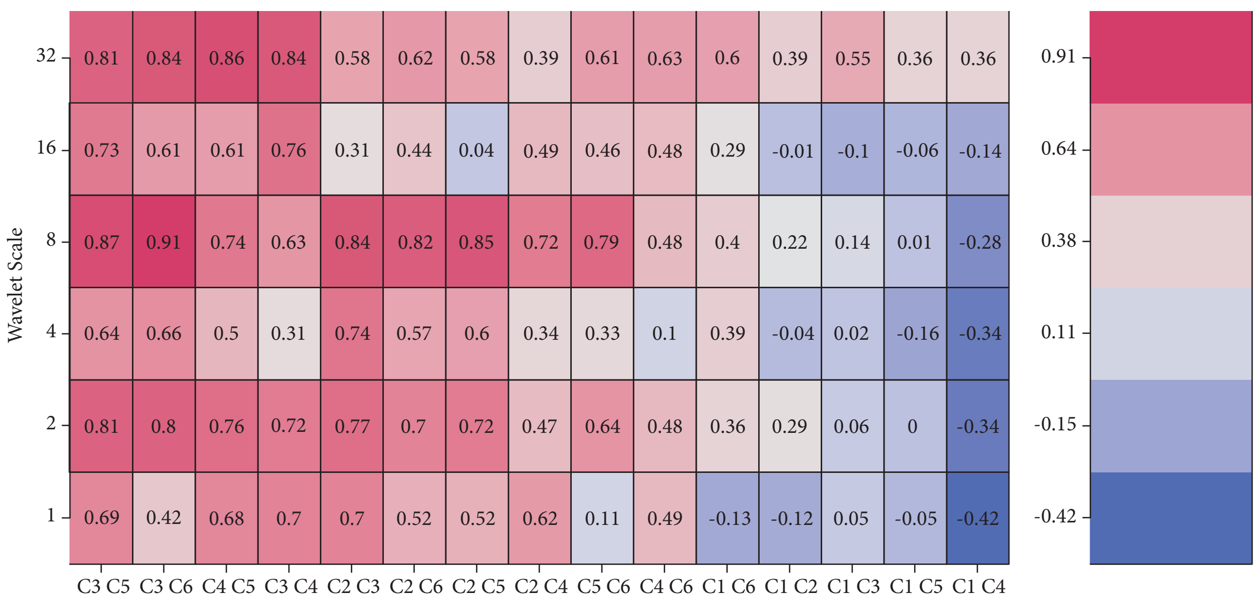

Figure 8: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are China (C1), India (C2), Indonesia (C3), Malaysia (C4), Thailand (C5), and Taiwan (C6).

find most positive relationships among the pairs, for instance, the comovements between Indonesia and Thailand; India and Indonesia; Indonesia and Malaysia; India and Taiwan, and among others. This suggests the uniformity in the systematic risk of Asia. However, there is a relatively lower levels of correlations between China and the remaining countries within the Asian region. This is so because China is among the top performing Asian countries in terms of nominal gross domestic product and features predominantly in the equities market, and thus, its systematic risk dynamics significantly segment from the remaining Asian countries. China is one of the very few countries in the emerging economies basket that has saw high earnings growth and high equity return against the backdrop of strong GDP growth [20]. However, the findings of Chen and Chiang [76] revealed that escalation of U.S. policy uncertainty has a significant adverse influence on Chinese stocks, thereby intensifying its systematic risk fluctuations as rightly confirmed from the descriptive statistics of the study. According to the volatility risk, "the EPU in Europe influences Asian countries the most and may be attributed to the extremely high trade dependence among these countries because the performance of international enterprises is mainly determined by the economic policies of their trading partners" [77]. Nonetheless, a portfolio with Chinese stock induces less shocks to other markets including global equities (see [20]), as shown by the negative comovements. This does not come as a surprise because the capital account of China is not fully liberalized. Despite the intention of the Chinese government to liberalize their capital account in recent years, the pace of liberalization remains ambiguous according to Liu, Spiegel and Zhang [78]. Consequently, portfolios inflows are more constrained in China. With a limited scope of investment assets, foreign financial institutions that invest in Chinese equities and bond markets do so through the Qualified Foreign Institutional Investor programs regarding a small quota [78, 79]. Restrictions on capital inflows within China are mostly

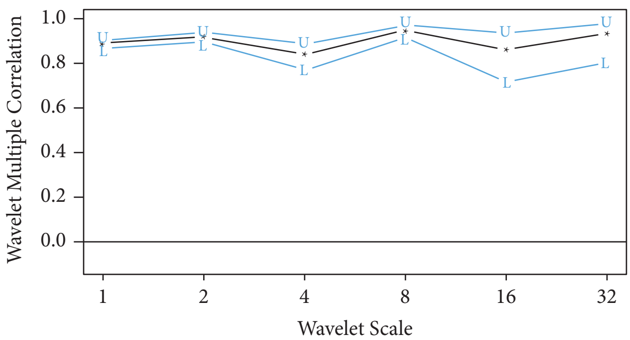

Figure 9: Wavelet multiple correlation between systematic risk of Asia (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

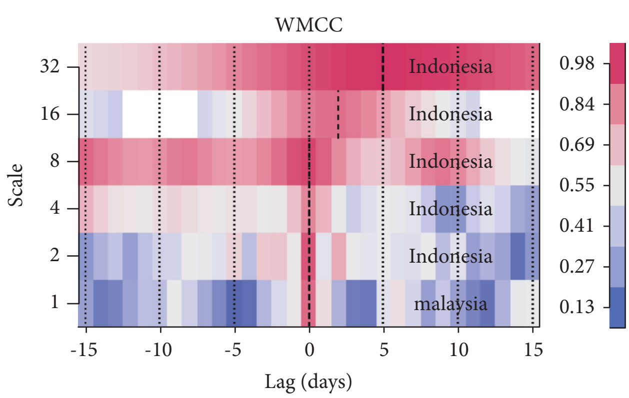

Figure 10: Wavelet multiple cross correlation between systematic risk of Asia (18/08/2010–03/11/2020).

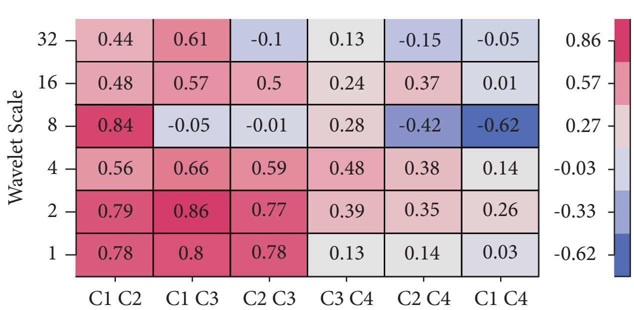

Figure 11: Wavelet bivariate correlations matrix (18/08/2010–03/11/2020). The codes for the variables are Czech Republic (C1), Greece (C2), Hungary (C3), and Russia (C4).

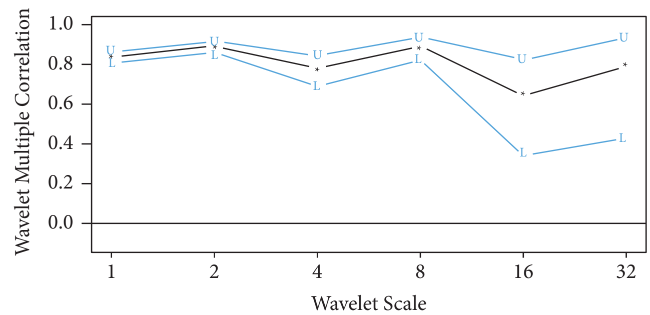

Figure 12: Wavelet multiple correlation between systematic risk of Europe (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

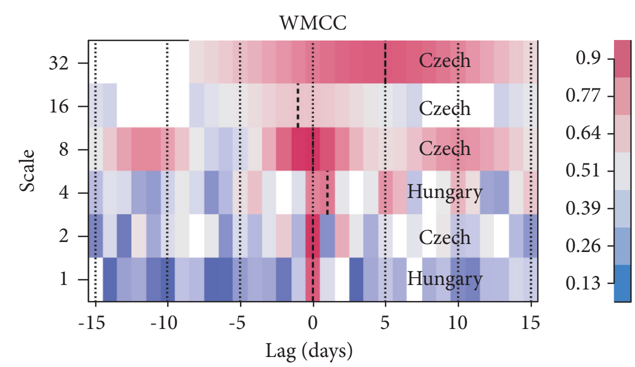

Figure 13: Wavelet multiple cross correlation between systematic risk of Europe 18/08/2010–03/11/2020).

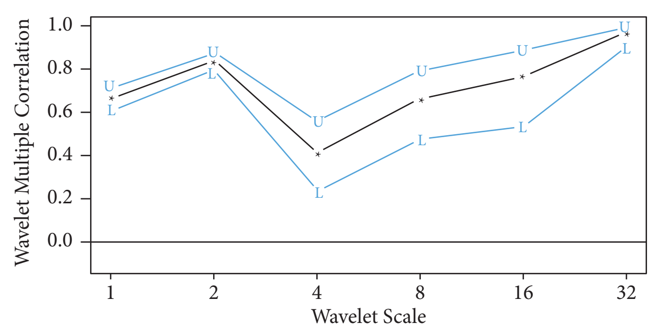

Figure 14: Wavelet multiple correlation between overall systematic risk of Emerging Markets (18/08/2010–03/11/2020). The blue lines denote upper (U) and lower limits (L) of the 95% confidence interval, respectively.

advanced to stabilize the currency, for instance, between 2000 and 2014. These are some of the practical reasons why China's systematic risk is less integrated.

Figure 9 represents the wavelet multiple correlation for the systematic nexus risk of Asia. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. In Figure 9, multiple correlations concentrate at large (above 0.82) at all-time scales. It begins with a correlation coefficient of about 0.88 at intraweek scale and attains minimum at fortnight (0.82) through to quarterly to biannual scale. The variation in the correlation continues until it reaches a peak of about 0.94 at biannual to annual scale. It can be analyzed that the systematic risk within Asia emerging markets is highly integrated. As a result, investors may less likely to reduce their portfolio risk when they form a portfolio within this region.

The wavelet multiple cross-correlation coefficients are presented in Table 5 depicting six wavelet scales. We find that systematic risk of Indonesia has the potential to lead and lag for most of the time scales (short-, medium-, and long-term dynamics). The systematic risk of Malaysia has the potential to lead or lag (at time 0) at intraweek scale. The systematic risk of Indonesia has the potential to lead and lag from weekly scale through to monthly scales but lags from

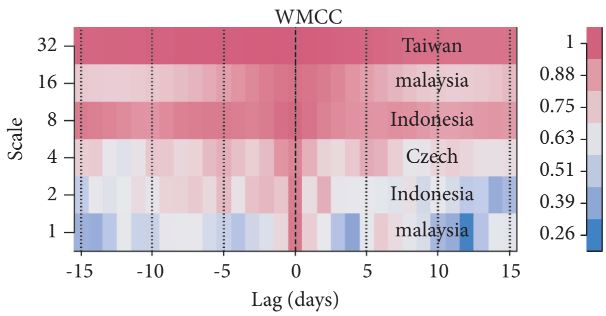

Figure 15: Wavelet multiple cross correlation between overall systematic risk of Emerging Markets (18/08/2010–03/11/2020).

Table 3: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lag (days)	Leading/lagging
1	0.717753473	0	Turkey
2	0.850666403	0	Turkey
3	0.429092917	0	Saudi Arabia
4	0.760799074	0	Qatar
5	0.784584139	−1	Qatar
6	0.973881045	−1	Qatar

Table 4: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lag (days)	Leading/lagging variable
1	0.461138768	−1	Brazil
2	0.56608047	0	Chile
3	0.809695585	0	Brazil
4	0.817564192	−7	Brazil
5	0.595102941	0	Colombia
6	0.839377245	7	Colombia

monthly to biannual scales, which depicts both short- to long-term dynamics. It could be seen that it is impossible for the systematic risk of China to lead or lag the systematic risk of the remaining Asian countries since the capital account of China is not fully liberalized [78]. Generally, the systematic risk of China, India, Thailand, and Taiwan is less connected with Indonesia and Malaysia. The outcome from Figure 10 indicates that the systematic risk of Indonesia lags in the long term, suggesting that it is the last nation within this region to respond to excess shocks.

4.1.4. Systematic Risk Comovement in the European Region. In Figure 11, we present the wavelet correlation matrix for systematic risk of Europe across the six scales. We find a mix of direct and inverse relationships among the pairs. The systematic risks of Czech Republic, Greece, and Hungary are highly correlated. However, Czech Republic and Greece exhibited the highest degree of comovement with coefficient fluctuating from 0.44 to 0.84. However, there are relatively lower levels of correlation between the systematic risk of Russia and the rest. Thus, the systematic risk of Russia demonstrated lower levels of correlation with the remaining countries in Europe. Accordingly, Russian stocks are most likely to experience diversification benefits. Generally, the

Table 5: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lags (days)	Leading/lagging variable
1	0.889421341	0	Malaysia
2	0.92081254	0	Indonesia
3	0.840432511	0	Indonesia
4	0.952318123	0	Indonesia
5	0.881861738	2	Indonesia
6	0.977211679	5	Indonesia

dynamic interdependence of the systematic risks is concentrated in the short term and medium term.

Figure 12 represents the wavelet multiple correlation for the systematic risk nexus of Europe. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. From Figure 12, multiple correlations fluctuate from 0.6 to 0.9, representing moderate to large comovements. It begins with a correlation coefficient of about 0.84 at intraweek scale and attains minimum (0.62) at monthly to quarterly scale. The variation in the correlation continues until it reaches scale 32 of about 0.78 at biannual scale.

The wavelet multiple cross correlation coefficients are presented in Table 6 depicting six wavelet scales. We find that systematic risk of Czech Republic has the potential to lead and/or lag at most time scales, and it can maximize the multiple cross-correlations from a linear perspective of combination of the remaining systematic risks representing the dynamics of short-, medium-, and long-run comovements. Similarly, Fedorova and Saleem [80] provided a strong evidence of direct linkages between the equity markets of Czech Republic and Hungary in terms of both returns and volatility. It can therefore be inferred from the outcome of Fedorova and Saleem [80] study that the dynamics of the stock returns and systematic risk returns of Czech Republic and Hungary are highly integrated in Europe. This suggests that the systematic risk of Czech Republic acts as a first mover and follower to external shocks from the medium to long term, whereas that of Hungary acts as a follower in the short-term.

4.1.5. Overall Systematic Risk Comovement of Emerging Market Economies. Figure 14 represents the wavelet multiple correlation for the systematic risk nexus of overall emerging markets. It could be argued that the nature of the correlation is far from being identical both along time and across frequencies. In Figure 14, multiple correlations concentrate at large (above 0.94) at all-time scales. It begins with a correlation coefficient of about 0.96 at intraweek scale and attains minimum at fortnight (0.94). The variation in the correlation continues until it reaches a peak of about 0.98 at biannual to annual scale. A critical glance of Figure 14 indicates that integration within emerging markets takes time before they converge in the long term. Consequently, systematic risk within emerging economies is amplified from long-term portfolio investment holdings. Investors who seek to minimize their portfolio risk within emerging markets are encouraged to capitalize on short- and medium-term equity

Table 6: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lags (days)	Leading/lagging variable
1	0.840230759	0	Hungary
2	0.892463734	0	Czech Republic
3	0.793805195	1	Hungary
4	0.896351128	0	Czech Republic
5	0.647701999	−1	Czech Republic
6	0.840041608	5	Czech Republic

Table 7: Wavelet multiple cross correlations (WMCC).

Scale	Localizations	Time lags (days)	Leader
1	0.958262149	0	Malaysia
2	0.948391306	0	Indonesia
3	0.958970521	0	Czech Republic
4	0.982771735	0	Indonesia
5	0.975318146	0	Malaysia
6	0.999798295	0	Taiwan

allocation and portfolio holdings. This exhibits the frequency-domain structure of the systematic risk integration in emerging market economies across the timescales.

The wavelet multiple cross correlation coefficients are presented in Table 7 depicting six wavelet scales. We find that systematic risk of Malaysia and Indonesia has the potential to lead for most of the time scales. The systematic risk of Malaysia has the potential to lead or lag (at time 0) specifically at intraweek scale and monthly to quarterly scale, Indonesia leads (at times) at weekly and monthly scales, Czech Republic has the potential to lead or lag at fortnight (at time 0), and Taiwan has the potential to lead or lag at quarterly to biannual scales (at time 0). This implies that the systematic risks of the twenty emerging market economies are driven by four countries, that is, Malaysia, Indonesia, Czech Republic, and Taiwan, at different investment horizons. That is, at each wavelet scale, an emerging country has a potential of driving or controlling the comovements, and there is a likelihood that uncertainty shocks are amplified within the leading countries in the systematic risk dynamics. To ensure risk minimization, global investors within these regions should hedge or use the correct asset allocation strategy.

4.2. Discussion. Evidence from the BCC demonstrated that the degree of correlation among the equity beta pairs for each country based on the regional analysis is scale-dependent. Generally, the equity betas of United Arab Emirates (Africa and Middle East), Argentina (Americas), China (Asia), and Russia (Europe) exhibit low degree of integration with other systematic risk returns from each region. The low correlations from these countries within their respective regions signify less risk transmission and should be included in a portfolio of assets in determining investment risks (see [20, 22, 26, 67]). Thus, domestic investors try to obtain diverse advantages from trading with other nations despite the contagion effect between financial markets that are highly interlinked after the onset of a shock [81, 82].

Likewise, from the WMC and WMCC analyses, the degree of integration among the equity betas increases with scale for most subregions and the emerging markets as a whole. This depicts that market connections increase as the investment horizon is prolonged revealing saturated markets with shocks. We indicate that the benefits of portfolio diversification seem greater at the short-run scale. As a result, systematic risk estimations in emerging markets require short time horizons [49] to benefit investors. This assertion agrees in terms of metal portfolio diversification as indicated by Tweneboah [73]. Also, in line with the study of Masih et al. [45], multiscale dynamics are predominant in the average beta of all GCC countries. The current study addresses the existence of multi-investment horizons due to multitrading strategies pursued by investors. With regard to other sectors, for instance, real estate global beta spillovers, the study of Liow and Newell [83] provides a substantial contribution to literature where global beta spillovers are significant and time-varying across the countries studied.

Specifically, it was revealed that it is impossible for the systematic risk of China to lead or lag the systematic risk of the remaining Asian countries. This is because the capital account of China is not fully liberalized [78] relative to other economies. In this regard, a portfolio with the Chinese stock transmits less shocks to other markets including global equities [20], irrespective of the fact that escalation of the U.S. policy uncertainty has a significant adverse influence on Chinese stocks to intensify its systematic risk fluctuations [76].

Furthermore, we analyzed the dynamics of each region with respect to which equity beta has the potential to serve as market leader in terms of systematic risk. From the scope of the study, Qatar (Africa & Middle East), Brazil (Americas), Indonesia (Asia), and Czech Republic (Europe) led at most of the time scales. The economic implication of this outcome is that the systematic risk in these countries is the first to respond and transmit shocks. Consequently, investors in these countries should carefully manage their investment portfolios. The dynamics to which the equity betas maximize the linear combination of the other equity betas for each region slightly changed when the overall analysis of the systematic risks was performed. Thus, the equity betas of Malaysia, Indonesia, Czech Republic, and Taiwan had the potential to lead or lag, but without a specific lead or lag. This reveals that emerging markets are highly interconnected [26, 58, 59].

Findings from the current study imply that a rise in systematic risk may produce a damaging influence on stock prices. This is because, theoretically, investors seek to be compensated with increased required rate of return during times of risk and uncertainties, which stimulates stock prices to fall, albeit the risk-return trade-off may not always be guaranteed. The increase in equity betas for most countries is consistent with the behavior of conservative investors who sell stock as risk hits the market. Conversely, "risk lover" investors at moments of increasing equity betas (systematic risk) will buy stocks at low prices and will be rewarded with risk premiums if stock prices reverse in the future [76, 84].

5. Conclusion

We employed the techniques of Kalman filter-based wavelet multiple approach. These tools enabled us to examine the degree of interdependence in the equity beta returns (systematic risk returns) of twenty emerging market economies and their implications for investing risk and risk management solutions such as asset allocation and portfolio diversification, but that cannot be attributed to specific risk of individual investments. With portfolio diversification, using the wavelet multiple analysis on the equity betas extracted with the help of Kalman filter, we minimized unsystematic risk to approach zero of different asset classes. Categorically, the paper makes a unique contribution to the interdependence literature by assessing regional and overall systematic risk (equity beta) lead/lag relationship in explaining the stock market shocks among the selected emerging markets. The preliminary analysis depicted high fluctuations of equity betas from 2010 to 2013, which can be attributed to the Eurozone crisis, and a positive shift in the equity beta index of most countries during the COVID-19 pandemic.

Outcomes from the BCC demonstrated that the degree of correlation among the equity beta pairs for most countries based on the regional analysis is scale-dependent. That is, the correlations fluctuate over time scales for each equity betas. In addition, there are less linkages between most emerging economies for the two-paired analysis, suggesting portfolio diversification between them. On the other hand, we found from the WMC and WMCC that the equity betas of Qatar, Brazil, Indonesia, and Czech Republic led at most of the time scales. The economic implication of this outcome is that the systematic risk in these countries is the first to respond and transmit shocks. However, we did not find a specific lead or lag when the overall analysis was performed. This accentuates the high integration of systematic risk returns of emerging markets economies. In general, by comparing the outcomes from the BCC to WMC and WMCC, it can be concluded that emerging markets are rather highly connected compositely than individually to significant markets such as Qatar, Brazil, Indonesia, Czech Republic, Malaysia, and Taiwan. We advocate that there are strong interdependencies among the systematic risks of emerging markets, and the benefit of portfolio diversification is scale-dependent, which is greater in the short run.

The interdependence structure among the systematic risks returns is heterogeneous and adaptive in line with the HMH [46] and AMH [47], which contradicts the principles of efficient market hypothesis by Fama [85]. Also, the spillover effects among similar or differing regional systematic risks are intensified by irrational investors' persisting search for contending risks to meet their portfolio goals to accentuate the competitive market hypothesis engineered by Owusu Junior, Frimpong et al. [23].

Moreover, the degree of integration among the equity betas increases with scale for most subregions and the emerging markets as a whole. This depicts that market connections increase as the investment horizon is prolonged, revealing saturated markets with shocks. In addition, the high comovements between systematic risks of most countries due to significant increase in cross-market linkages are in broad consensus with the Contagion studies. Consequently, markets with augmented linkages indicate that shocks in one market are easily transferable to other markets. Indeed, knowledge of capital account liberalization in emerging markets offers many prospects along with challenges for the economic policymakers. Policy makers, governments, and international unions across the globe should fine-tune their economic policies to restore these betas to an appropriate level required by investors.

In line with the MPT [2], investors who seek to minimize their portfolio risks can do so in the short term. In this manner, international investors can observe the markets and take advantage of the scale-dependent comovement dynamics. The outcome from this study dynamically reflects the systematic risk of emerging markets opportunity set, and to help investors meet global and regional asset allocation needs. However, as with equity allocation decisions, investors should be cautious and understand the risks of moving away from a market-capitalization-weighted portfolio.

It is recommended that emerging markets should improve their depth of investments by encouraging the involvement of investors, especially institutional investors. Integrating the emerging market economies and facilitating cross listing can minimize investing risk, improve liquidity, and mitigate thin trading. For instance, application of prudent liquidity policies is needed to enhance resilience to systematic risks susceptibilities in the long term. Moreover, the introduction of the market maker role and invigorating the trading mechanism in the emerging market economies can minimize the issues of transaction cost, plummet excessive volatility, and make prices faithfully represent their value. To end with, public offerings should be intensified to contribute to the expansion of trading in emerging markets by local and foreign savings, which may serve as diversification opportunities for global investors. It is established from extant literature that uncertainties have the potential of impacting stock markets, which may invariably heighten the systematic risk of a given country, and this poses a challenge for emerging markets to maximize their investment climate via efficient financial reforms in order to attract global investors.

The current study is limited to the use of frequency-dependent analysis, revealing only intrinsic times (investment horizons). Hence, absence of calendar time dimension in this study becomes a caveat of this study. Further studies may concentrate on network analysis towards revealing the centrality of the systematic risk dynamics, and the investigation of macroeconomic variables impact on systematic risk in emerging market economies. Also, analysis may be analyzed through a time-frequency technique to reveal the impacts of various markets events, which must have caused a structural break or regime switch worthy of research in this area. Moreover, the increasing awareness of transfer entropy, specifically, at less probability events as illustrated by most empirical literature [44, 57, 86] in finance, may contribute to the discussion on systematic risk interdependencies.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] A. Ali and K. N. Badhani, "Beta-Anomaly: evidence from the Indian equity market," *Asia-Pacific Financial Markets*, vol. 28, no. 1, pp. 1–24, 2020.

[2] H. Markowitz, "Portfolio selection," *The Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.

[3] W. F. Sharpe, "Capital asset prices: a theory of market equilibrium under conditions of risk," *The Journal of Finance*, vol. 19, no. 3, pp. 425–442, 1964.

[4] J. L. Treynor, *Toward a Theory of Market Value of Risky Assets*, Wiley Online Library, Hoboken, NJ, USA, 1961.

[5] J. L. Treynor, "Jack treynor's toward a theory of market value of risky assets," *SSRN Electronic Journal*, 1962.

[6] B. G. Malkiel and 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.

[7] R. A. Haugen and A. J. Heins, "Risk and the rate of return on financial assets: some old wine in new bottles," *Journal of Financial and Quantitative Analysis*, vol. 10, no. 5, pp. 775–784, 1975.

[8] K. B. Diether, C. J. Malloy, and A. Scherbina, "Differences of opinion and the cross section of stock returns," *The Journal of Finance*, vol. 57, no. 5, pp. 2113–2141, 2002.

[9] A. Ang, R. J. Hodrick, Y. Xing, and X. Zhang, "The cross-section of volatility and expected returns," *The Journal of Finance*, vol. 61, no. 1, pp. 259–299, 2006.

[10] N. L. Baker and R. A. Haugen, "Low risk stocks outperform within all observable markets of the world," *SSRN Electronic Journal*, 2012.

[11] A. Frazzini and L. H. Pedersen, "Betting against beta," *Journal of Financial Economics*, vol. 111, no. 1, pp. 1–25, 2014.

[12] M. H. Miller and M. Scholes, "Rates of return in relation to risk: a reexamination of some recent findings," *Studies in the theory of capital markets*, vol. 23, pp. 768–783, 1972.

[13] M. Baker, B. Bradley, and J. Wurgler, "Benchmarks as limits to arbitrage: understanding the low-volatility anomaly," *Financial Analysts Journal*, vol. 67, no. 1, pp. 40–54, 2011.

[14] S. Das, H. Markowitz, J. Scheid, and M. Statman, "Portfolio optimization with mental accounts," *Journal of Financial and Quantitative Analysis*, vol. 45, no. 2, pp. 311–334, 2010.

[15] H. Konno and H. Yamazaki, "Mean-absolute deviation portfolio optimization model and its applications to Tokyo stock market," *Management Science*, vol. 37, no. 5, pp. 519–531, 1991.

[16] E. Kwame Austro Gozah, E. Neebo Wiah, A. Buabeng, and P. Yaw Addai Yeboah, "Portfolio optimization for stock market in Ghana using value-at-risk (VaR)," *American Journal of Mathematical and Computer Modelling*, vol. 5, no. 3, pp. 61–69, 2020.

[17] A. Zaremba and A. Czapkiewicz, "Digesting anomalies in emerging European markets: a comparison of factor pricing models," *Emerging Markets Review*, vol. 31, pp. 1–15, 2017.

[18] A. M. Adam and E. N. Gyamfi, "Time-varying world integration of the African stock markets: a Kalman filter approach," *Investment Management and Financial Innovations*, vol. 12, no. 3, pp. 175–181, 2015.

[19] D. Igan, A. M. Kutan, and A. Mirzaei, "The real effects of capital inflows in emerging markets," *Journal of Banking & Finance*, vol. 119, Article ID 105933, 2020.

[20] J. Hsu, X. Liu, and P. Wool, "Should you have more China in your portfolio? Putting common arguments for increased China exposure to the test," *The Journal of Index Investing*, vol. 11, no. 3, pp. 48–61, 2020.

[21] Msci, "MSCI emerging markets," 2021, https://www.msci.com.

[22] 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*, pp. 1–19, 2021.

[23] 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.

[24] E. Asafo-Adjei, E. Boateng, Z. Isshaq, A. A.-A. Idun, P. Owusu Junior, and A. M. Adam, "Financial sector and economic growth amid external uncertainty shocks: insights into emerging economies," *PLoS One*, vol. 16, no. 11, Article ID e0259303, 2021.

[25] M. E. H. Arouri and P. Foulquier, "Financial market integration: theory and empirical results," *Economic Modelling*, vol. 29, no. 2, pp. 382–394, 2012.

[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, 15 pages, 2021b.

[27] R. Koepke, "What drives capital flows to emerging markets? a survey of the empirical literature," *Journal of Economic Surveys*, vol. 33, no. 2, pp. 516–540, 2019.

[28] M. A. Kose, E. S. Prasad, and M. E. Terrones, "Does financial globalization promote risk sharing?" *Journal of Development Economics*, vol. 89, no. 2, pp. 258–270, 2009.

[29] D. Furceri and P. Loungani, "The distributional effects of capital account liberalization," *Journal of Development Economics*, vol. 130, pp. 127–144, 2018.

[30] M. A. ur Rehman and M. A. Hayat, "Capital account liberalization and economic growth," *Pakistan Economic and Social Review*, vol. 55, no. 1, pp. 299–313, 2017.

[31] R. Engle and B. Kelly, "Dynamic equicorrelation," *Journal of Business & Economic Statistics*, vol. 30, no. 2, pp. 212–228, 2012.

[32] N. R. Xu, "Global risk aversion and international return comovements," *SSRN Electronic Journal*, 2019.

[33] N. T. Hung, "Return equicorrelation and dynamic spillovers between Central and Eastern European, and World stock markets, 2010–2019," *Regional Statistics*, vol. 12, no. 01, pp. 159–192, 2022.

[34] D. T. N. Huy and N. T. Hang, "Factors that affect stock price and beta CAPM of vietnam banks and enhancing management information system - case of Asia commercial bank," *Revista Gestão Inovação e Tecnologias*, vol. 11, no. 2, pp. 302–308, 2021.

[35] J. C. Ruíz Barrezueta, J. E. Altamirano Flores, and L. B. Tonon Ordóñez, "Aplicación del CAPM en Mercados Emergentes: una revisión teórica," *Podium*, vol. 39, pp. 53–70, 2021.

[36] K. Gkillas, A. Tsagkanos, and D. I. Vortelinos, "Integration and risk contagion in financial crises: evidence from

international stock markets," *Journal of Business Research*, vol. 104, pp. 350–365, 2019.

[37] Y. Atilgan, T. G. Bali, K. O. Demirtas, and A. D. Gunaydin, "Downside beta and equity returns around the world," *Journal of Portfolio Management*, vol. 44, no. 7, pp. 39–54, 2018.

[38] P. Owusu Junior and I. Alagidede, "Risks in emerging markets equities: time-varying versus spatial risk analysis," *Physica A: Statistical Mechanics and its Applications*, vol. 542, Article ID 123474, 2020.

[39] P. Owusu Junior, A. K. Tiwari, G. Tweneboah, and E. Asafo-Adjei, "GAS and GARCH based value-at-risk modeling of precious metals," *Resources Policy*, vol. 75, Article ID 102456, 2022.

[40] K. E. Strandmoe, *Investigating The Merits of Using a Kalman Filter In Equity Beta Estimation* ,, Master's Thesis, Handelshøyskolen BI, Master's Thesis, Handelshøyskolen BI, 2018.

[41] T. Choudhry and H. Wu, "Forecasting ability of GARCH vs Kalman filter method: evidence from daily UK time-varying beta," *Journal of Forecasting*, vol. 27, no. 8, pp. 670–689, 2008.

[42] F. Lie, R. Brooks, and R. Faff, "Modelling the equity beta risk of Australian financial sector companies," *Australian Economic Papers*, vol. 39, no. 3, pp. 301–311, 2000.

[43] G. Tweneboah, "Dynamic interdependence of industrial metal price returns: evidence from wavelet multiple correlations," *Physica A: Statistical Mechanics and Its Applications*, vol. 527, Article ID 121153, 2019a.

[44] 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, 2021c.

[45] M. Masih, M. Alzahrani, and O. Al-Titi, "Systematic risk and time scales: new evidence from an application of wavelet approach to the emerging Gulf stock markets," *International Review of Financial Analysis*, vol. 19, no. 1, pp. 10–18, 2010.

[46] U. A. Müller, M. M. Dacorogna, R. D. Davé, R. B. Olsen, O. V. Pictet, and J. E. Von Weizsäcker, "Volatilities of different time resolutions—analyzing the dynamics of market," *Journal of Empirical Finance*, vol. 4, 1997.

[47] A. W. Lo, "The adaptive markets hypothesis," *Journal of Portfolio Management*, vol. 30, no. 5, pp. 15–29, 2004.

[48] K. Yan, H. Yan, and R. Gupta, "Are GARCH and DCC values of 10 cryptocurrencies affected by COVID-19?" *Journal of Risk and Financial Management*, vol. 15, no. 3, p. 113, 2022.

[49] U. Arief, "Systematic risk in emerging markets: a high-frequency approach," *JDM (Jurnal Dinamika Manajemen)*, vol. 12, no. 1, pp. 1–11, 2021.

[50] S. Ling and K. Zhu, "Self-weighted LSE and residual-based QMLE of ARMA-GARCH models," *Journal of Risk and Financial Management*, vol. 15, no. 2, p. 90, 2022.

[51] A. K. Mishra and K. Ghate, "Dynamic connectedness in non-ferrous commodity markets: evidence from India using TVP-VAR and DCC-GARCH approaches," *Resources Policy*, vol. 76, Article ID 102572, 2022.

[52] M. Nazeri-Tahroudi, Y. Ramezani, C. De Michele, and R. Mirabbasi, "Bivariate simulation of potential evapotranspiration using copula-GARCH model," *Water Resources Management*, vol. 36, pp. 1–18, 2022.

[53] P. Manopimoke, S. Prukumpai, and Y. Sethapramote, "Dynamic connectedness in emerging Asian equity markets," *Banking and Finance Issues in Emerging Markets*, vol. 25, 2018.

[54] E. Asafo-Adjei, S. Frimpong, P. Owusu Junior, A. M. Adam, E. Boateng, and R. O. Abosompim, "Multi-frequency information flow between global commodities and uncertainties: evidence from COVID-19 pandemic," *Complexity*, vol. 2022, 2022.

[55] P. M. Osei and A. Adam, "Threshold cointegration approach for assessing the impact of US economic policy uncertainty on monetary policy decision of african countries," *Scientific Annals of Economics and Business*, vol. 68, no. 4, pp. 509–528, 2021.

[56] A. M. Adam, E. N. Gyamfi, K. A. Kyei, S. Moyo, and R. S. Gill, "A new EEMD-effective transfer entropy-based methodology for exchange rate market information transmission in Southern Africa Development Community," *Complexity*, vol. 2021, Article ID 3096620, 22 pages, 2021.

[57] A. Bossman, S. K. Agyei, P. Owusu Junior et al., "Flights-to-and-from-Quality with islamic and conventional bonds in the COVID-19 pandemic era: ICEEMDAN-based transfer entropy," *Complexity*, vol. 2022, Article ID 1027495, 25 pages, 2022.

[58] R. I. Ahmed, G. Zhao, and U. Habiba, "Dynamics of return linkages and asymmetric volatility spillovers among Asian emerging stock markets," *The Chinese Economy*, vol. 55, no. 2, pp. 1–12, 2021.

[59] K. Shi, "Spillovers of stock markets among the BRICS: new evidence in time and frequency domains before the outbreak of COVID-19 pandemic," *Journal of Risk and Financial Management*, vol. 14, no. 3, p. 112, 2021.

[60] P. Owusu Junior, A. M. Adam, and G. Tweneboah, "Connectedness of cryptocurrencies and gold returns: evidence from frequency-dependent quantile regressions," *Cogent Economics & Finance*, vol. 8, no. 1, Article ID 1804037, 2020.

[61] R. Gençay, F. Selçuk, and B. J. Whitcher, *An Introduction to Wavelets and Other Filtering Methods in Finance and Economics*, Elsevier, Amsterdam, Netherlands, 2001.

[62] D. B. Percival and A. T. Walden, *Wavelet Methods for Time Series Analysis*, Cambridge University Press, Cambridge, UK, 2000.

[63] R. E. Kalman, *A New Approach to Linear Filtering and Prediction Problems*, Wiley, Hoboken, New Jersey, NJ, USA, 1960.

[64] J. Lintner, "Security prices, risk, and maximal gains from diversification," *The Journal of Finance*, vol. 20, no. 4, pp. 587–615, 1965.

[65] R. W. Faff, D. Hillier, and J. Hillier, "Time varying beta risk: an analysis of alternative modelling techniques," *Journal of Business Finance & Accounting*, vol. 27, no. 5-6, pp. 523–554, 2000.

[66] J. Fernández-Macho, "Wavelet multiple correlation and cross-correlation: a multiscale analysis of Eurozone stock markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 391, no. 4, pp. 1097–1104, 2012.

[67] E. Asafo-Adjei, D. Agyapong, S. K. Agyei, S. Frimpong, R. Djimatey, and A. M. Adam, "Economic policy uncertainty and stock returns of Africa: a wavelet coherence analysis," *Discrete Dynamics in Nature and Society*, vol. 2020, Article ID 8846507, 8 pages, 2020.

[68] V. Arora and M. Cerisola, "How does US monetary policy influence sovereign spreads in emerging markets?" *IMF Staff Papers*, vol. 48, no. 3, pp. 474–498, 2001.

[69] J. Fang, B. R. Marshall, N. H. Nguyen, and N. Visaltanachoti, "Do stocks outperform treasury bills in international markets?" *Finance Research Letters*, vol. 40, Article ID 101710, 2021.

[70] D. A. Cerdeiro and A. Komaromi, "Financial openness and capital inflows to emerging markets: in search of robust evidence," *International Monetary Fund*, 2019.

[71] C. P. Nguyen, T. V. H. Nguyen, and C. Schinckus, "Institutions, economic openness and stock return co-movements: an empirical investigation in emerging markets," *Finance Research Letters*, vol. 28, pp. 137–147, 2019.

[72] E. Araújo, R. Brito, and A. Z. Sanvicente, "Long-term stock returns in Brazil: volatile equity returns for US-like investors," *International Journal of Finance & Economics*, vol. 26, 2020.

[73] G. Tweneboah, P. Owusu Junior, and E. K. Oseifuah, "Integration of major african stock markets: evidence from multiscale wavelets correlation," *Academy of Accounting and Financial Studies Journal*, vol. 23, no. 6, pp. 1–15, 2019.

[74] R. Joseph and M. Fernandez, "Growth of stock market in the UAE through merger: a comparative study of GCC stock markets," *Accounting and Finance Research*, vol. 5, no. 3, p. 190, 2016.

[75] A. K. Panda and S. Nanda, "Market linkages and conditional correlation between the stock markets of South and Central America," *Journal of Financial Economic Policy*, vol. 9, 2017.

[76] X. Chen and T. C. Chiang, "Empirical investigation of changes in policy uncertainty on stock returns-Evidence from China's market," *Research in International Business and Finance*, vol. 53, Article ID 101183, 2020.

[77] I.-C. Tsai, "The source of global stock market risk: a viewpoint of economic policy uncertainty," *Economic Modelling*, vol. 60, pp. 122–131, 2017.

[78] Z. Liu, M. M. Spiegel, and J. Zhang, "Optimal capital account liberalization in China," *Journal of Monetary Economics*, vol. 117, pp. 1041–1061, 2021.

[79] N. Lardy and P. Douglass, *Capital Account Liberalization and the Role of the Renminbi*, Routledge, England, UK, 2013.

[80] E. Fedorova and K. Saleem, "Volatility spillovers between stock and currency markets: evidence from emerging Eastern Europe," *SSRN Electronic Journal*, vol. 69, 2010.

[81] E. H. Nazlioğlu and K. Ö. K. Dündar, "Contagion in Turkish stock market: evidences from developed and emerging markets," *Ege Academic Review*, vol. 21, no. 4, pp. 407–425, 2021.

[82] K. Malik, S. Sharma, and M. Kaur, "Measuring contagion during COVID-19 through volatility spillovers of BRIC countries using diagonal BEKK approach," *Journal of Economics Studies*, vol. 49, no. 2, 2021.

[83] K. H. Liow and G. Newell, "Real estate global beta and spillovers: an international study," *Economic Modelling*, vol. 59, pp. 297–313, 2016.

[84] G. Koutmos, "Positive feedback trading: a review," *Review of Behavioral Finance*, vol. 6, 2014.

[85] 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.

[86] 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.