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Exploring the Dynamic Relationship Between Stock Market Indices and Exchange Rates: During and After the Crises—Insights from G20 and Asian Countries

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Abstract

The global financial landscape has been profoundly affected by crises such as the COVID-19 pandemic, the Russia-Ukraine war, and geopolitical trade disputes, leading to heightened volatility in stock and foreign exchange markets. This study examines the dynamic spillovers between stock indices and exchange rates across G20 countries and key Asian economies, including Thailand and China, from January 2012 to June 2023. Employing the DCC-GJR-GARCH(1,1) model with one-step estimation, which efficiently captures time-varying correlations in high-dimensional datasets, the study provides a comprehensive analysis of crisis-induced market fluctuations. Findings reveal significant shifts in correlation structures, volatility persistence, and spillover effects, particularly during major crises, emphasizing the role of economic uncertainty indicators such as the VIX. These insights are critical for policymakers, investors, and financial analysts, offering a deeper understanding of risk transmission and aiding in strategic decision-making for market stability, portfolio diversification, and crisis preparedness.

Keywords: stock market index, exchange rate, economic crisis, volatility, G20 countries, SDG.

1. Introduction

The global economic and financial landscape is continuously evolving, shaping economic growth across nations. Sustainable development depends on robust funding sources that support business expansion, trade, and international investments. Financial institutions, particularly stock markets, play a pivotal role in facilitating capital flow and serving as intermediaries between investors and industries in need of capital. Large economies, such as China, the United States, and India, exert significant influence on the global economy, making their stock markets attractive to investors seeking long-term returns.

However, economic crises—such as the COVID-19 pandemic, the Russia-Ukraine war, and trade disputes—have introduced substantial volatility into stock markets worldwide. For example, Thailand’s capital market experienced significant fluctuations during the COVID-19 crisis, with the SET index dropping sharply in early 2020. Similar trends were observed in other countries, as crises undermine corporate productivity, weaken investor confidence, and contribute to declining stock prices.

The interconnectedness of global trade and investment further complicates financial market stability. Foreign investment significantly influences capital markets and affects exchange rate movements through cross-border capital flows. Exchange rate volatility, driven by speculative trading and economic uncertainty, impacts corporate performance and stock market indices, particularly in economies with high exposure to international trade and investment. The complex relationship between stock markets and exchange rates becomes particularly evident during periods of financial distress, necessitating a deeper examination of their dynamic interactions.

Historical events, such as the 1997 Asian Financial Crisis, underscore the risks associated with exchange rate speculation and its profound impact on Thailand and other Asian economies. These crises force businesses to adapt to currency fluctuations, directly affecting stock market performance. The COVID-19 pandemic further demonstrated how global financial instability leads to capital outflows, currency depreciation, and heightened market volatility. Prior studies, such as Kamonchai et al. (2020), explored the stock market-exchange rate relationship in the Asia-Pacific region, highlighting that stock markets tend to absorb volatility better than currency markets. This correlation intensifies during crises, reinforcing the interdependence of global financial systems.

While previous studies have examined volatility and correlation in financial markets, many fail to address the evolving nature of risk transmission across stock markets and exchange rates in a high-dimensional setting. Most existing research relies on static correlation models or focuses on individual markets, limiting insights into dynamic spillover effects, particularly during financial crises. Furthermore, studies often overlook the role of the VIX (Volatility Index) as a global risk gauge and its impact on financial interdependencies.

This study fills these gaps by applying the one-step estimation DCC-GARCH model to capture time-varying volatility spillovers across stock indices and exchange rates in G20 economies and key Asian financial hubs like Thailand and China. Unlike traditional models such as BEKK or GO-GARCH, which suffer from excessive parameterization and computational inefficiency in high-dimensional data, DCC-GARCH offers a more scalable and flexible approach, allowing for more precise estimation of correlation structures without sacrificing model efficiency. Given that financial markets are increasingly interconnected, understanding how VIX-driven volatility spillovers affect both equity and currency markets is essential for risk management and policy responses.

By integrating VIX into a high-dimensional correlation analysis, this study provides a more robust framework for assessing global financial stability, particularly during crises. This structured approach enhances understanding of how volatility propagates across markets and informs more effective hedging strategies and monetary policies in volatile economic conditions.

2. Literature Review

The relationship between stock markets and exchange rates has been widely studied, particularly in the context of financial market integration, volatility transmission, and crisis periods. Taylor and Tonks (1989) examined the impact of exchange rate deregulation in the UK on stock market integration with international markets. Their findings revealed that post-deregulation, the UK market became more connected to developed economies such as Germany, Japan, and the Netherlands. This integration provided more investment opportunities but also reduced the benefits of international diversification due to higher long-term covariances, as noted by Grubel and Fadner (1971). Panton et al. (1976) and Ripley (1973) contributed early empirical evidence on international stock market co-movements, forming the foundation for contemporary financial integration studies.

Kamonchai et al. (2020) analyzed the dynamic relationship between stock markets and exchange rates in the Asia-Pacific region, finding significant causality between the two, except in China. Their study demonstrated that stock markets in this region exhibited greater resilience to volatility compared to exchange rates. Additionally, financial linkages with major economies such as the UK, Germany, and the US strengthened during crises, underscoring the growing interdependence of global markets. Rujirarangsan et al. (2020) further investigated dynamic volatility spillovers between stock markets and exchange rates in the Asia-Pacific region, providing evidence of evolving interdependencies in response to external shocks.

Kanas (1998) investigated the long-term cointegration between US and European stock markets, concluding that their integration was weak, in contrast to previous studies that suggested strong financial linkages. However, subsequent studies, including those by Longin and Solnik (1995), provided evidence that financial crises, such as the 1997 Asian Financial Crisis and the US subprime mortgage crisis, significantly increased global financial correlations, supporting the contagion hypothesis. Forbes and Rigobon (2002) also found that increased market interdependencies do not always indicate contagion but could reflect pre-existing linkages that intensify during crises. Thampanya et al. (2020) analyzed the determinants of stock return volatility in ASEAN-5 countries, demonstrating the importance of behavioral and fundamental factors in shaping market fluctuations.

More recent research has focused on the COVID-19 pandemic's impact on financial markets worldwide, particularly in the US, Japan, Thailand, and China. Studies show that heightened volatility in the US market significantly influenced Asian financial markets, with China and Thailand being particularly sensitive (Sharif et al., 2020). Moreover, during periods of economic uncertainty, investors tend to shift capital toward safe-haven assets, such as US Treasury Bills, gold, and even digital currencies like Bitcoin, highlighting changes in investment behavior during crises (Al-Awadhi et al., 2020).

Chiang et al. (2013) examined the spillover effects of the subprime mortgage crisis in BRICV stock markets and found that crisis-induced volatility significantly alters optimal asset allocation strategies.

Engle (1982) initially introduced the ARCH framework, emphasizing the importance of capturing time-varying volatility structures in financial markets. To capture the time-varying nature of market relationships, Bollerslev (1986) also expanded the ARCH model to GARCH, which models volatility through past data. Engle (2002) later introduced the DCC-GARCH model, allowing for dynamic correlation analysis between financial assets. These models have been extensively applied in empirical research to assess evolving stock market-exchange rate relationships, particularly during economic crises.

While conditional volatility models and dynamic conditional correlation (DCC) models are widely used in financial research, their ability to capture the impact of specific crises or country-specific factors remains limited. To enhance the study's robustness, additional econometric methods should be incorporated to link volatility and correlation estimation with broader economic and financial determinants.

For example, the multivariate GARCH model, such as BEKK-GARCH (Engle & Kroner, 1995), is commonly employed to analyze the direction of volatility spillovers and asymmetries in risk transmission. This approach offers a more flexible framework compared to the standard DCC-GARCH model, particularly in assessing shock persistence and inter-market influences during financial crises. BEKK-GARCH has been extensively used to investigate market dependencies and contagion effects (Caporale et al., 2019). Additionally, Wu et al. (2015) distinguished between slow-burn spillovers and fast contagion effects in international stock markets, emphasizing the varying speeds of risk transmission.

Additionally, estimating volatility and dynamic correlation series in relation to key macroeconomic determinants, like the VIX Index (Chicago Board Options Exchange Volatility Index), which serves as a proxy for global risk sentiment and investor uncertainty (Bekaert et al., 2013), provides a more comprehensive understanding of market behavior during crisis periods, highlighting how external shocks amplify risk transmission across economies. Pastpipatkul et al. (2015) explored the spillover effects of Quantitative Easing in emerging markets, showing how global liquidity policies influence financial interdependence.

Furthermore, the Diebold-Yilmaz Spillover Index (Diebold & Yilmaz, 2012) is an advanced methodology that quantifies volatility transmission across assets, industries, or countries. Unlike traditional GARCH models, which focus on pairwise relationships, the spillover index measures the intensity and direction of cross-market influence. This approach has been applied extensively in analyzing crisis-induced interdependencies, including during the 2008 Global Financial Crisis, the COVID-19 pandemic, and geopolitical conflicts (Antonakakis & Gabauer, 2017). Corsetti et al. (2004) developed theoretical models explaining currency crises and speculative attacks, highlighting the role of large traders in influencing exchange rate fluctuations.

Other econometric methods that could enhance the study's contribution include:

- Quantile Regression Models: Used to assess the asymmetric impact of financial shocks across different market conditions (Koenker & Hallock, 2001).

- Wavelet-Based Coherence Analysis: Offers a time-frequency decomposition of stock market-exchange rate linkages, particularly useful for capturing short-term versus long-term dependencies (Rua & Nunes, 2009).
- Markov-Switching GARCH Models: Incorporate regime changes in financial volatility, allowing for identification of high-risk versus stable periods (Hamilton & Susmel, 1994).

This study builds on these methodologies by employing the DCC-GARCH model to analyze volatility dynamics in stock markets and exchange rates, offering insights into financial stability during global crises. However, due to the original work's reliance on the two-step estimation procedure, which may not fully meet consistency requirements and could introduce estimation inefficiencies, this study adopts a one-step estimation approach to address this issue. The one-step estimation method ensures greater statistical efficiency and parameter consistency by simultaneously estimating all model parameters rather than separating the estimation of conditional correlations and variance structures as done in the two-step approach (Aielli, 2013). Additionally, given the complexity of analyzing more than 30 financial variables, including stock indices and currency pairs, the DCC-GARCH model is particularly suitable as it efficiently models time-varying correlations without the computational burden of estimating an excessive number of parameters, making it ideal for capturing dynamic relationships in high-dimensional datasets (Laurent et al. 2012).

3. Methodology and Data

The study examines the dynamic relationship between stock market indices and exchange rates during crises in Asian and G20 countries using the DCC-GARCH model. It incorporates Simple-GARCH, EGARCH, and GJRGARCH models to analyze volatility and shifting relationships over time, revealing crisis impacts on major economies.

3.1 GARCH Models

The GARCH (Generalized Autoregressive Conditionally Heteroscedasticity) model is used for analyzing data volatility when the volatility of time series data is non-stationary. A single volatility value cannot represent the data accurately, especially in cases of non-constant volatility. Therefore, this model is effective in mitigating issues of autocorrelation and non-constant variance. This often occurs in studies where there is a large amount of data used in the study, especially financial securities information that has fluctuations involved.

The GARCH model consists of two main equations: The Mean Equation and the Conditional Variance Equation. The Mean Equation in the standard model can be expressed as follows:

$$r_{i,t} = \mu_i + \varepsilon_{i,t},\ i = 1,2,\dots,n, \tag{1}$$

and

$$\varepsilon_{i,t} = \sqrt{h_{i,t}}z_{i,t}, \tag{2}$$

The return of stock i at time t, represented by $r_{i,t}, \mu_i$, is the return's average, which is a constant term, and the residual term $\varepsilon_{i,t} \cdot z_{i,t}$ is a standardized residual. Both $\varepsilon_{i,t}$ and $z_{i,t}$ are independent and identically distributed *(i.i.d.)* random variables, which is a property of *i.i.d.*, $E(z_{i,t}) = 0$ and $E\left(z_{i,t}z_{i,t}^T\right) = I$.

At time t, the return of stock i is represented by $r_{i,t}$, where μ_i represents the average return, which is a constant term. The residual term $\varepsilon_{i,t}$ reflects the deviation of actual returns from the average return. The standardized residual term $z_{i,t}$ satisfies the properties of independent and identically distributed *(i.i.d.)* random variables, with a mean of 0 and a variance equal to $\left(E\left(z_{i,t}z_{i,t}^T\right) = I\right)$.

Under the simple GARCH(1,1) process, the equation below describes the conditional variance or conditional volatility of returns at time t:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{3}$$

In the variance equation, parameters ω_i, α_i, and β_i must be positive. α_i captures the ARCH effect, indicating volatility changes based on past data, while β_i represents the GARCH effect, reflecting the persistence of conditional variance over time.

3.2 Glosten-Jagannathan-Runkle-GARCH

Consider a return time series $r_t = \mu + \varepsilon_t$, where μ is the expected return and ε_t is a zero-mean white noise. Despite being serially uncorrelated, the series ε_t does not need to be serially independent. For instance, it can present conditional heteroskedasticity. The Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model assumes a specific parametric form for this conditional heteroskedasticity.

The GJR-GARCH is an alternative GARCH model that providing leverage term γ_i. The leverage term helps capture the volatility's bad news and good news. When the error $\varepsilon_{i,t-1}$ is negative, $I_{i,t-1}$ equals 1; otherwise, it is 0.

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_i I_{i,t-1} h_{i,t-1} \tag{4}$$

where

$$I_{i,t-1} = \begin{cases} 1 \text{ if } \varepsilon_{i,t-1} < 0 \\ 0 \text{ if } \varepsilon_{i,t-1} \geq 0 \end{cases} \tag{5}$$

3.3 Exponential GARCH (EGARCH)

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, originally introduced by Nelson (1991), has been proven to be an efficient tool for capturing two key characteristics in financial time series: asymmetric effects and leverage effects. This model adeptly accommodates both positive and negative impacts and handles volatility effects without the need for non-negativity constraints. From the results, the variance of the EGARCH(1,1) model can be expressed as follows:

$$\log\left(h_{i,t}\right) = \omega_{\mathrm{i}} + \alpha_i \varepsilon_{i,t-1} + \gamma_i\left(\left|\varepsilon_{i,t-1}\right|\right) + \beta_i \log\left(h_{i,t-1}\right) \tag{6}$$

The equation consists of coefficients α_i, which capture both positive and negative impacts (indicated by the sign), and γ_j, which capture the impact of size asymmetry. The coefficients ω_i, α_i, and γ_i are not subject to any constraints. However, the coefficient β_i must satisfy two conditions, i.e., it must be positive and less than 1, to ensure the stability of the model. These conditions are critical to maintaining the reliability and meaningfulness of exponential GARCH models in capturing asymmetry and leverage effects in efficient financial time series data.

3.4 Dynamic Conditional Correlation

The DCC model proposed by Engle (2002) is a complex framework for analyzing time-varying correlations between n stocks. This model stands out for its realism compared to traditional correlation models, which often assume constant correlations between the two assets. In the DCC model, correlations between assets are examined using the conditional correlation matrix R_t and the conditional covariance matrix H_t. Covariance is not only influenced by its past values but is also influenced by the conditional covariance at time t, which is expressed as Ψ_{t-1}. This set can represent past innovation or past return values.

The covariance matrix H_t, which represents $E[r_t r_t' \mid \Psi_{t-1}]$, is calculated using the covariance technique. Estimated values are appropriate and can be expressed as

$$H_t = D_t R_t D_t, \tag{7}$$

where D_t is a diagonal matrix representing the time-varying conditional variance $h_{i,t}$ under the GARCH(1,1) process. Using D_t as the diagonal matrix allows the conditional variance to vary with time, consistent with the dynamics of the GARCH model. Variability evolves based on past data, and the size of the matrix is $n \times n$ is illustrated as follows:

$$D_t = \begin{bmatrix} \sqrt{h_{1,t}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2,t}} & 0 & \cdots & 0 \\ 0 & 0 & \sqrt{h_{3,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{h_{n,t}} \end{bmatrix} \tag{8}$$

The correlation matrix R_t is a symmetric positive semi-definite matrix that represents the relationship between assets i and j. The elements in the correlation matrix ρ_{ij} reflect the relationship between assets i and j, expressed as:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \cdots & \rho_{2n,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1,t} & \rho_{n2,t} & \cdots & 1 \end{bmatrix} \tag{9}$$

Another representation of R_t is given by

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{10}$$

where

$$Q_t = (1 - a - b)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \tag{11}$$

The above equation illustrates the structure of the DCC(1,1) model, where the matrix $\bar{Q}$ represents the unconditional covariance matrix of dimension $n \times n$. To ensure that the matrix h_t is positive, definite, and clear, it is necessary that $a \geq 0$ and $b \geq 0$. Additionally, to satisfy the condition $|\rho_{ij}| = \frac{|q_{ij,t}|}{\sqrt{q_{ij,t}q_{jj,t}}} \leq 1$, it uses Q_t^* which is a diagonal matrix with the diagonal elements of Q_t, denoted as

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22,t}} & 0 & \cdots & 0 \\ 0 & 0 & \sqrt{q_{33,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \sqrt{q_{nn,t}} \end{bmatrix} \tag{12}$$

where component $\sqrt{q_{ii,t}}$ represents the volatility of the relevant asset i at time t.

The parameter set Θ comprises various parameters (both in GARCH and DCC models) such as $a, b, v, \delta, \phi, \omega_i, \alpha_i, \beta_i, \gamma_i, \ldots$ and can be calculated using the DCC probability function by using maximum likelihood estimation.

$$L(\Theta) = -\frac{1}{2}\sum_{t=1}^{T} (\text{nlog}(2\pi) + \log|D_t| + \log|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t) \tag{13}$$

Maximum likelihood estimation is used to find parameter values that best explain the observed data. However, Engel's (2002) DCC model suffers from the disadvantage that many of the parameter estimates lack consistency due to the two-step process.

The one-step estimation approach offers several advantages over the two-step estimation and other alternative econometric models. First, one-step estimation DCC-GARCH offers greater efficiency by simultaneously optimizing all parameters, reducing bias, and improving computational performance in high-dimensional datasets (Engle & Sheppard, 2001; Laurent et al., 2012). It ensures consistency and robust asymptotic properties, avoiding the standard error inconsistencies seen in two-step methods (Engle, 2002; Hafner & Franses, 2009). Studies confirm that DCC models provide more accurate correlation estimates than BEKK, which struggles with large datasets (VaR in High Dimensional Systems - A Conditional Correlation Approach).

Additionally, one-step estimation is more adaptive to structural shifts during financial crises, effectively capturing time-varying dependencies (Hafner & Franses, 2009; Efficient Factor GARCH Models and Factor-DCC Models). Unlike the two-step method, which loses information by estimating parameters separately, one-step DCC-GARCH integrates variance and correlation dynamics, leading to better risk transmission modeling (Caporin & McAleer, 2012; Laurent et al., 2010).

Compared to BEKK-GARCH, which is parameter-heavy and prone to overfitting, one-step DCC-GARCH remains parsimonious while capturing dynamic correlations efficiently (Silvennoinen & Teräsvirta, 2009). It also outperforms alternative models such as the Diebold-Yilmaz Spillover Index, which focuses on market shocks but lacks volatility persistence modeling, and Wavelet-Based Analysis, which captures frequency dependencies but lacks probabilistic inference (Diebold & Yilmaz, 2012; Rua & Nunes, 2009).

3.5 Data

This study examines the dynamic relationship between stock market and exchange rate returns relative to the US dollar (USD) across G20 countries, including the G8 nations: United Kingdom (Ex_GBP), Canada (Ex_CAD), France (Ex_EUR), Italy (Ex_EUR), Japan (Ex_JPY), Germany (Ex_EUR), Russia (Ex_RUB), and the United States (Ex_USD), as well as emerging economies like Argentina (Ex_ARS), Australia (Ex_AUD), Brazil (Ex_BRL), China (Ex_CNY), India (Ex_INR), Indonesia (Ex_IDR), Mexico (Ex_MXN), Saudi Arabia (Ex_SAR), South Africa (Ex_ZAR), South Korea (Ex_KRW), and Turkey (Ex_TRY). Additionally, it includes non-G20 countries in Asia, focusing on Thailand (Ex_THB) and China (Ex_CNY).

Stock indices include the SET (Thailand), MERVAL (Argentina), ASX 200 (Australia), Bovespa (Brazil), TSX (Canada), Nikkei 225 (Japan), FTSE (UK), and others. Moreover, we include the VIX Index, which is a proxy for global risk sentiment and investor uncertainty. All 31 variables from Yahoo Finance span from January 3, 2012, to June 30, 2023, comprising 2,137 observations and covering events like the Russia-Ukraine conflict and the COVID-19 pandemic. Summary statistics in Table 1 reveal negative skewness and high kurtosis, indicating deviations from normal distribution. Jarque-Bera and Augmented Dickey-Fuller tests confirm stationarity across all returns.

Table 1. Descriptive statistics of returns

	Ex_THB	Ex_ARS	Ex_AUD	Ex_BRL	Ex_CAD	Ex_CNY
Mean	0.0001	0.0030	-0.0003	0.0007	0.0002	0.0001
Minimum	-0.0304	-0.0960	-0.0604	-0.0903	-0.0303	-0.0186
Maximum	0.0458	0.2911	0.0477	0.0784	0.0285	0.0214
SD	0.0060	0.0149	0.0089	0.0146	0.0066	0.0036
Skewness	0.5844	9.0375	-0.2917	0.3064	0.0120	0.1407

Kurtosis	6.8010	145.6631	4.0164	4.3850	1.9944	5.9322
Jarque Bera	2,600.6*	1,175,136*	900.4*	1,071.4*	217.98*	1,926.7*
ADF Test	-10.39*	-9.601*	-10.997*	-10.35*	-10.875*	-8.269*
	Ex_EUR	Ex_INR	Ex_IDR	Ex_JPY	Ex_MXN	Ex_RUB
Mean	-0.0001	0.0003	0.0003	0.0003	0.0002	0.0008
Minimum	-0.0322	-0.0368	-0.2125	-0.0466	-0.0655	-4.6260
Maximum	0.0304	0.0373	0.2122	0.0735	0.0829	4.6646
SD	0.0067	0.0057	0.0165	0.0084	0.0107	0.2117
Skewness	0.0231	0.4203	0.0098	0.5120	0.8578	0.2103
Kurtosis	2.8900	6.1851	108.4690	9.8604	7.2100	394.1954
Jarque Bera	457.11*	2,128.2*	641,770*	5,365.1*	2,999.4*	8,475,490*
ADF Test	-10.99*	-11.175*	-12.9*	-10.475*	-10.272*	-17.599*
	Ex_SAR	Ex_ZAR	Ex_KRW	Ex_TRY	Ex_GBP	SET
Mean	0.0000	0.0005	0.0001	0.0020	-0.0001	-0.0000
Minimum	-0.1257	-0.0456	-0.0429	-0.2090	-0.0953	-0.1143
Maximum	0.1269	0.0746	0.0517	0.1830	0.0430	0.0944
SD	0.0051	0.0136	0.0079	0.0166	0.0084	0.0136
Skewness	0.3250	0.5420	0.2646	1.0201	-1.3405	-1.3021
Kurtosis	595.0436	2.2740	3.7587	47.5711	16.0822	13.1614
Jarque Bera	19,312,375*	347.22*	787.71*	123,680*	14,506*	9,824.1*
ADF Test	-17.477*	-11.802*	-10.763*	-9.395*	-10.408*	-10.453*

Note: * denotes a strong or higher rejection of the null hypothesis, according to the Minimum Bayes Factor (MBF) (Maneejuk and Yamaka, 2021).

Table 1. (continued)

	MERVAL	ASX	Bovespa	TSX	Hang_Seng	EURO
Mean	0.0038	0.0003	0.0006	0.0003	-0.0001	0.0004
Minimum	-2.9091	-0.1586	-0.1826	-0.1485	-0.1026	-0.1464
Maximum	3.0290	0.0645	0.1286	0.0941	0.0914	0.1488
SD	0.1213	0.0130	0.0208	0.0126	0.0177	0.0175
Skewness	1.2516	-2.0272	-0.7644	-2.4237	-0.2553	-0.9288
Kurtosis	547.5916	22.9686	10.0496	29.5256	3.1962	13.9544
Jarque Bera	16,355,391*	29,681*	5,640.9*	48,843*	573.01*	10,816*

ADF Test	-12.731*	-10.677*	-9.920*	-11.753*	-10.175*	-11.15*
	Nifty	Jakarta	Nikkei	IPC	MOEX	Tadawul
Mean	0.0009	0.0003	0.0008	0.0002	0.0005	0.0004
Minimum	-0.0867	-0.1184	-0.0940	-0.0906	-0.5341	-0.1316
Maximum	0.0959	0.0731	0.1201	0.0790	0.1664	0.0855
SD	0.0145	0.0143	0.0182	0.0134	0.0237	0.0158
Skewness	-0.3678	-1.2578	-0.3638	-0.4751	-8.7509	-1.2049
Kurtosis	5.7887	10.4365	5.6268	5.1391	199.0286	10.3001
Jarque Bera	1,860*	6,290.9*	1,758.5*	1,492.2*	2,177,333*	6,108.2*
ADF Test	-10.486*	-10.677*	-10.952*	-10.338*	-11.296*	-9.994*
	JSE	KOSPI	BIST	FTSE	VIX	
Mean	0.0005	0.0002	-0.0021	0.0001	-0.0002	
Minimum	-0.1023	-0.0924	-4.6835	-0.1319	-0.2998	
Maximum	0.1711	0.1457	0.1599	0.1213	0.7682	
SD	0.0155	0.0144	0.1317	0.0139	0.0697	
Skewness	0.4542	0.0388	-34.3876	-0.9803	1.3074	
Kurtosis	15.0882	12.9680	1219.1221	16.1964	9.0687	
Jarque Bera	12,469*	9,179.1*	81,321,898*	14,525*	13,392*	
ADF Test	-11.621*	-10.156*	-10.803*	-11.36*	-17.775*	

Note: * denotes a strong or higher rejection of the null hypothesis, according to the Minimum Bayes Factor (MBF) (Maneejuk and Yamaka, 2021).

4. Estimation Results

The researcher analyzed volatility and correlations using various DCC-GARCH models with different distribution assumptions: Normal (NORM), Skewed Normal (SNORM), Student's t (STD), and Skewed Student's t (SSTD). The goal was to determine the best-fitting model by comparing Goodness of Fit metrics, such as the Bayesian Information Criterion (BIC), and to assess whether the model incorporating VIX outperforms the model without VIX in our analysis. Table 2 shows the BIC results for three GARCH(1,1) models, revealing that the GJR-GARCH(1,1) with VIX model under the Skewed Normal distribution had the lowest BIC value, making it the best-fitting model for finding dynamic conditional correlations (DCC). Then, all estimated parameters shown in this study will be estimated by the optimal model. The model that includes VIX outperforms the one without it, suggesting that incorporating VIX enhances the ability to capture volatility dynamics more effectively. This indicates that including VIX in the model provides valuable information for studying market volatility.

Table 2. BIC estimates for DCC-GARCH-type(1,1) models under six distributions

DCC-GARCH(1,1) without VIX				
	NORM	SNORM	STD	SSTD
SGARCH	-230.7004	-230.4812	-230.3242	-229.9711
GJRGARCH	-230.8028	-230.5581	-230.2680	-229.8728
EGARCH	-230.8274	-230.6951	-227.0234	-221.3246
DCC-GARCH(1,1) with VIX				
	NORM	SNORM	STD	SSTD
SGARCH	-261.4114	-261.5104	-259.8532	-259.4262
GJRGARCH	-261.5116	-261.5201	**-261.5226**	-261.3916
EGARCH	-261.3692	-261.0430	-257.3947	-258.3947

Table 3 reports the results of estimating the relationships between return variables for each security using the GJR-GARCH(1,1) model under the Skewed Normal distribution. The parameters showed high volatility persistence ($\propto +\beta > 0.9$) across most stock and currency markets from 2012 to 2023, except for Turkey's and the UK's stock indexes. Additionally, the leverage term (γ) had a statistically significant positive sign in the stock, indicating that negative shocks have a greater impact on returns, particularly in currency and stock markets.

Table 3. Results of DCC- GJR-GARCH(1,1) under STD distribution model

		Ex_THB	Ex_ARS	Ex_AUD	Ex_BRL	Ex_CAD
Mean Eq.	μ_i	-0.0003*	0.001	-0.0002*	0.0004*	0.0001
GJR-GARCH	ω_i	0.0000	0.0000	0.0000	0.0000	0.0000
	α_i	0.0289*	0.0504	0.0091*	0.087	0.0374*
	β_i	0.9087*	0.9005	0.9702*	0.9242*	0.9595*
	γ_{i_i}	0.1038*	0.0483	0.0301*	-0.0473	-0.0159
		Ex_CNY	Ex_EUR	Ex_INR	Ex_IDR	Ex_JPY
Mean Eq.	μ_i	-0.0001	-0.0001	0.0002	-0.0001	0.0002*
GJR-GARCH	ω_i	0.0000	0.0000	0.0000	0.0000*	0.0000
	α_i	0.0635*	0.0137*	0.0811	0.1346*	0.0523
	β_i	0.9441*	0.9716*	0.9217	0.7746*	0.9429*
	γ_{i_i}	-0.0406	0.023*	-0.0261	0.1203*	-0.0005
		Ex_MXN	Ex_RUB	Ex_SAR	Ex_ZAR	Ex_KRW
Mean Eq.	μ_i	0.0002	0.0003*	0.0000	0.0005*	-0.0001
GJR-GARCH	ω_i	0.0000	0.0000	0.0000	0.0000*	0.0000
	α_i	0.1193*	0.1937*	0.0501*	0.0318*	0.0328
	β_i	0.895*	0.8175*	0.9025*	0.9782*	0.9434*
	γ_{i_i}	-0.0718*	-0.0233	0.0459*	-0.0297*	0.0236

Note: * denotes a strong or higher rejection of the null hypothesis, according to the Minimum Bayes Factor (MBF) (Maneejuk and Yamaka, 2021).

Table 3. (continued)

		Ex_TRY	Ex_GBP	SET	MERVAL	ASX
Mean Eq.	μ_i	0.0005*	-0.0001	0.0000	0.0013*	0.0000
GJR-GARCH	ω_i	0.0000	0.0000	0.0000	0.0000*	0.0000*
	α_i	0.141*	0.0269	0.0212*	0.1614*	0.0000
	β_i	0.9093*	0.9424*	0.9318*	0.8304*	0.9254*
	γ_{i_i}	-0.0994*	0.0396*	0.0708*	-0.0314	0.0986*
		Bovespa	TSX	Hang_Seng	EURO	Nifty
Mean Eq.	μ_i	0.0001	0.0000	-0.0001	-0.0001	0.0003*
GJR-GARCH	ω_i	0.0000*	0.0000	0.0000	0.0000	0.0000*
	α_i	0.0105*	0.0000	0.0067	0.0000	0.0000

	β_i	0.9214*	0.9126*	0.9488*	0.9062*	0.9236*
	γ_{i_i}	0.0689*	0.1382*	0.0564*	0.1489*	0.1076*
		Jakarta	Nikkei	IPC	MOEX	Tadawul
Mean Eq.	μ_i	-0.0001	0.0002	-0.0001	0.0000	0.0002
GJR-GARCH	ω_i	0.0000	0.0000*	0.0000	0.0000	0.0000
	α_i	0.0113	0.0215*	0.0075	0.0950*	0.0089*
	β_i	0.9294*	0.8876*	0.9428*	0.9103*	0.9117*
	γ_{i_i}	0.0722*	0.1079*	0.0741*	-0.0203	0.1036*
		JSE	KOSPI	BIST	FTSE	VIX
Mean Eq.	μ_i	0.0000	-0.0001	0.0006*	-0.0002	0.0049*
GJR-GARCH	ω_i	0.0000	0.0000	0.0000*	0.0000*	0.0005*
	α_i	0.0011	0.0175	0.0661*	0.0000	0.2217*
	β_i	0.9305*	0.9235*	0.7262*	0.8797*	0.8039*
	γ_{i_i}	0.1052	0.0711	0.1108*	0.1648*	-0.2508*
DCC	a	0.0057*				
	b	0.9734*				

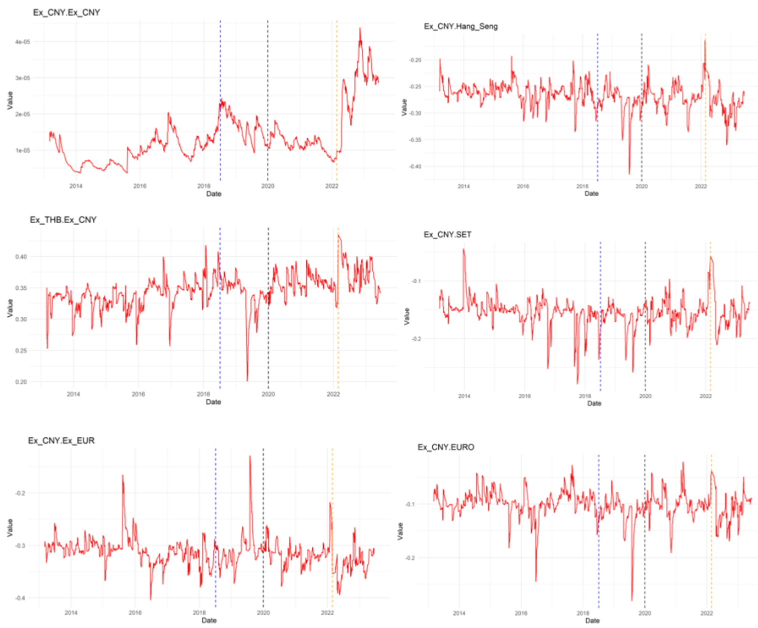
Note: * denotes a strong or higher rejection of the null hypothesis, according to the Minimum Bayes Factor (MBF) (Maneejuk and Yamaka, 2021).

In this study, we examined over a thousand correlation pairs using the DCC model. The estimated DCC parameters indicate a high degree of correlation persistence, with a + b = 0.9791, suggesting that past correlations strongly influence current dynamics.

Our findings reveal patterns across three major events: the US-China trade tensions, the COVID-19 pandemic, and the Ukrainian-Russian war. Firstly, we observed that the impact of the US-China trade tensions on DCC was relatively stable and less fluctuating compared to the other events. Secondly, we observed significant fluctuations in DCC among global stock markets and their respective currencies during the COVID-19 pandemic. Thirdly, the ongoing Ukrainian-Russian war significantly disrupted correlation pairs involving the Russian stock index and other currencies, indicating a substantial shock to financial markets.

The DCC during US-China trade tensions was relatively stable and less volatile compared to other events. While there was increased volatility in Chinese yuan returns leading up to the trade barriers (Figure 1), yuan volatility gradually decreased over time after the policies were enacted.

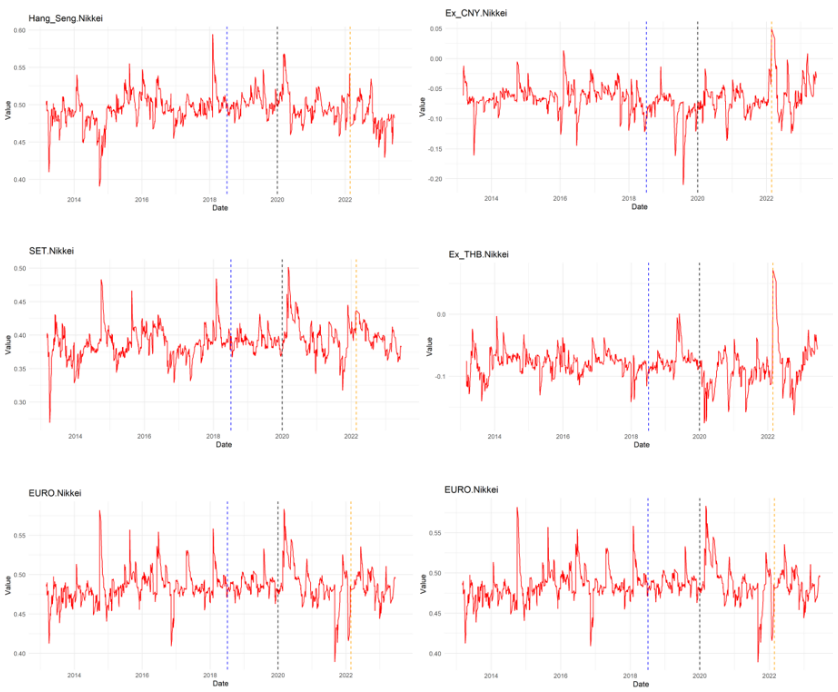
Figure 1. Volatilities and DCC between the Chinese currency and other stock/currency



Notes: The vertical blue dashed line marks the commencement of the US-China trade war, the black dashed line represents the date of the COVID-19 outbreak, and the orange dashed line indicates the onset of the Russian-Ukrainian conflict.

To better understand the impact of the COVID-19 pandemic, this crisis caused significant fluctuations in DCC among global stock markets and their respective currencies. Market volatility surged, and stock markets experienced sharp declines as COVID-19 cases rose in the US and Europe, highlighting the interconnectedness of global markets during crises. Figure 2 illustrates the daily return correlations between Japan's Nikkei index and the Hang Seng, Euro STOXX 50, and the Stock Exchange of Thailand indices. During the pandemic, especially after March 2020, there was a large increase in correlation among these markets. The connections between the Nikkei and currencies like the Chinese yuan and Thai baht became stronger, showing that the pandemic had a big effect on how these currencies moved along with the Japanese stock market.

Figure 2. DCC between Nikkei and other stock/currency

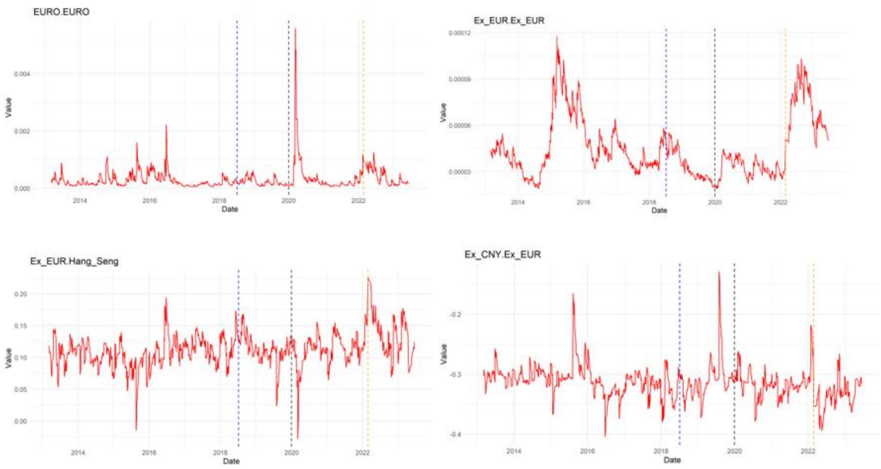


Notes: The vertical blue dashed line marks the commencement of the US-China trade war, the black dashed line represents the date of the COVID-19 outbreak, and the orange dashed line indicates the onset of the Russian-Ukrainian conflict.

To explore the impact of the Ukrainian-Russian war in more detail, we observed distinct patterns in European financial markets. The ongoing conflict significantly disrupted correlation pairs involving the Russian stock index and other currencies, indicating a substantial shock to financial markets. In European financial markets, shifts in investor sentiment due to geopolitical developments had immediate effects on stock prices (Figure 3). The Euro experienced significant fluctuations driven by concerns over sanctions on Russia, impacts on European economies, and changes in global trade flows.

The DCC between the Euro, the Hang Seng index, and the Chinese yuan unveiled the heightened sensitivity to geopolitical tensions.

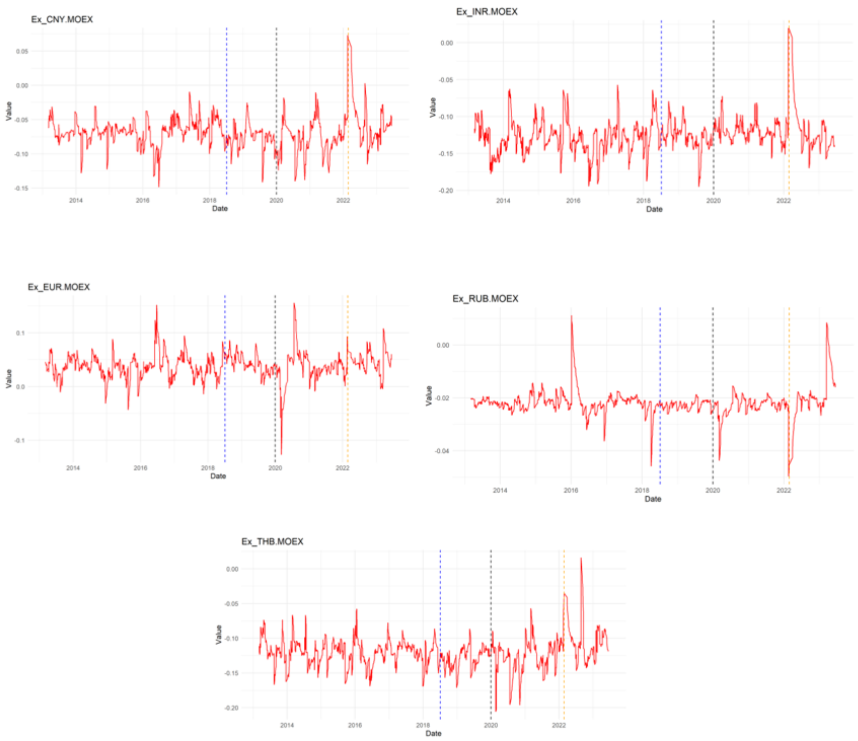
Figure 3. Volatilities and DCC between EU currency and other stock



Notes: The vertical blue dashed line marks the commencement of the US-China trade war, the black dashed line represents the date of the COVID-19 outbreak, and the orange dashed line indicates the onset of the Russian-Ukrainian conflict.

Increased volatility in the DCC between the Euro and the Hang Seng index showed a stronger correlation with Hong Kong stocks, reflecting broader global risk sentiment. Figure 4 demonstrates significant shifts in DCCs involving the Russian stock index with the Chinese yuan, Thai baht, Indian rupee, and Euro, underscoring how the conflict impacted Russia's currency relationships with major trading partners and emerging market currencies.

Figure 4. DCC between MOEX and other currency



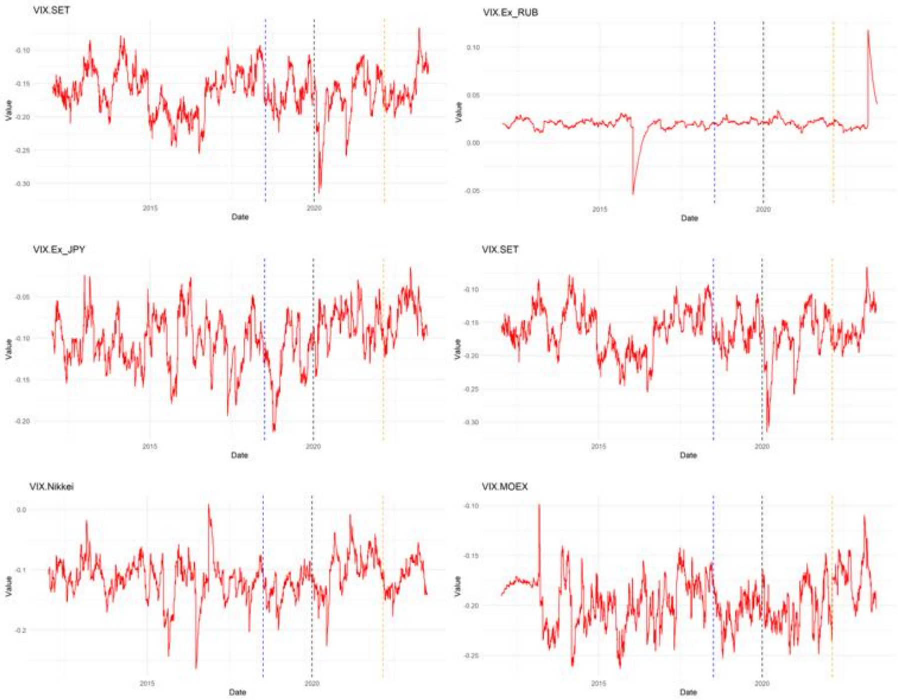
Notes: The vertical blue dashed line marks the commencement of the US-China trade war, the black dashed line represents the date of the COVID-19 outbreak, and the orange dashed line indicates the onset of the Russian-Ukrainian conflict.

Additionally, during the Ukrainian-Russian war, we found a reversal in the earlier trend of decreasing yuan volatility (Figure 4). The dynamic correlation between Chinese yuan returns and the Hang Seng index decreased, indicating greater divergence. There was also a noticeable reduction in the DCC between Chinese yuan returns and the Euro, reflecting the yuan's depreciation against the US dollar while the Euro remained comparatively stable.

Figure 5 illustrates the DCC between the VIX and various financial assets, including the Stock Exchange of Thailand (SET), Russian Ruble (RUB), Japanese Yen (JPY), Nikkei 225 Index, and the Moscow Exchange (MOEX), among others, over time. The red lines represent the time-varying correlation coefficients, showing how the relationship between VIX and each asset evolves. Periods of positive correlation indicate that increased market volatility (higher

VIX) coincides with rising asset volatility, suggesting that these assets move in tandem during times of uncertainty. Conversely, negative correlations suggest a flight-to-safety effect, where rising VIX leads to asset depreciation, particularly for risk-sensitive currencies and stock indices.

Figure 5. DCC between VIX and currencies/stock indices



Notes: The vertical blue dashed line marks the commencement of the US-China trade war, the black dashed line represents the date of the COVID-19 outbreak, and the orange dashed line indicates the onset of the Russian-Ukrainian conflict.

Key observations include strong positive correlations between the Russian Ruble and the Moscow Exchange, possibly reflecting their susceptibility to external shocks, such as geopolitical risks. Meanwhile, the Japanese Yen and the Nikkei 225 Index exhibit fluctuating correlations, indicating that the safe-haven nature of the yen influences its relationship with VIX over time. The dotted vertical lines highlight major economic or geopolitical events, such as the COVID-19 crisis in 2020 and other financial shocks, which significantly impact correlations. These findings underscore the varying sensitivity of global markets to volatility, with some assets amplifying risk while others serve as hedges against uncertainty. The above observations highlight how global financial markets react sensitively to geopolitical events, revealing intricate interdependencies across regions and currencies during periods of heightened uncertainty. Investors reassessed risks in affected regions, adjusted portfolios accordingly, and closely monitored commodity prices like oil and gas due to their significance in the events.

Our findings emphasize the profound impact that major global crises have on the relationships between stock markets and exchange rates. Understanding these dynamic correlations is important for investors, policymakers, and financial analysts as they navigate the complexities of an increasingly interconnected global economy. By employing the DCC-GJR-GARCH model, we provide deeper insights into how crises reshape financial market interdependencies, which is vital for effective risk management and strategic decision-making.

5. Conclusion

This study critically examines the complex and evolving relationship between stock markets and exchange rates across G20 economies and key Asian financial hubs from January 2012 to June 2023, particularly during major global crises. Unlike traditional research that relies on static or two-step estimation models, this study advances the methodology by employing a one-step Dynamic Conditional Correlation-GARCH model with GJR-GARCH(1,1) specification and Skewed Normal distribution. This improves estimation efficiency, mitigates bias, and enhances the model's ability to capture time-varying volatility spillovers, particularly in high-dimensional financial datasets with over 30 stock indices and currency pairs. Given the limitations of BEKK-GARCH—such as excessive parameterization and computational inefficiencies—DCC-GARCH emerges as the superior approach for analyzing dynamic financial interdependencies.

The findings underscore critical vulnerabilities in global financial markets. During the COVID-19 pandemic, stock-exchange rate correlations surged, reflecting unprecedented market stress and heightened systemic risk, particularly in European and Asian financial indices such as Nikkei 225, Euro, and Hang Seng. The Ukrainian-Russian conflict triggered severe market disruptions, with the Russian Ruble (Ex_RUB) and Moscow Exchange (MOEX) exhibiting strong positive correlations with VIX, indicating heightened exposure to external shocks and geopolitical instability. In contrast, the Japanese Yen (Ex_JPY) and the Nikkei 225 Index displayed fluctuating correlations, reinforcing the yen's role as a safe-haven asset in crisis periods. The US-China trade tensions, while initially causing financial uncertainty, resulted in more stable correlations over time, suggesting markets adapted to prolonged geopolitical risks rather than reacting with immediate volatility spikes. These divergent market reactions challenge conventional assumptions about crisis-driven financial contagion, highlighting that not all crises induce uniform financial spillovers across regions.

Econometric analysis further confirms persistent volatility and asymmetric market reactions to risk events. The DCC parameter estimates ($a + b = 0.9791$) indicate a high degree of correlation persistence, meaning that past correlations strongly influence current market behavior. Additionally, the results validate that negative news shocks have a greater impact on market volatility than positive news, reinforcing the presence of asymmetric volatility transmission. This has critical implications for financial stability, as markets exhibit nonlinear responses to crises, amplifying systemic risks in unpredictable ways. The one-step estimation approach used in this study enhances statistical efficiency, reduces estimation bias, and ensures a more robust modeling framework, making it superior to traditional two-step estimation methods, which suffer from inefficiencies and inconsistencies in large datasets.

From a policy and risk management perspective, the findings highlight the urgent need for dynamic, data-driven risk monitoring frameworks. The inclusion of VIX as a volatility benchmark demonstrates its significant role in capturing global risk sentiment and predicting volatility spillovers. Policymakers must closely monitor intermarket dependencies, as currency-market linkages exhibit heightened sensitivity during financial crises. Investors should reassess risk management strategies, as certain assets act as amplifiers of volatility while others provide hedging opportunities. The study's adoption of one-step DCC-GARCH modeling offers a powerful alternative to computationally demanding models such as BEKK-GARCH, allowing for a more precise, scalable, and timely assessment of global financial risks.

Future research must move beyond simplistic correlation-based models and incorporate real-time financial indicators, monetary policy adjustments, and alternative asset classes such as commodities and bonds to develop a more holistic understanding of financial contagion and crisis-driven volatility transmission. The study's findings challenge the adequacy of conventional risk models and reaffirm that dynamic, high-dimensional approaches such as DCC-GARCH with one-step estimation are essential for capturing the true complexity of modern financial systems.

Acknowledgments

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