

Financial Contagion in Stock Markets in the Era of the Russian-Ukraine War, Trump Tariff Dispute, and COVID-19 Uncertainties

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ABSTRACT

This study employs nonlinear time-varying correlation methodologies to analyze high-frequency stock market data for a group of developed and emerging markets between December 16, 2019, and July 31, 2025, amid uncertainties related to politics, geopolitics, trade, and the COVID-19 pandemic. COVID-19, the Russia-Ukraine war, and uncertainties surrounding US President Trump's second term have become a new type of systematic risk for stock market participants globally, leading to weaker external demand and fragile financial markets. We identify a substantial increase in correlation among certain country pairs during the coronavirus crisis, indicating heightened contagion. In contrast, trade-policy-based shocks during the Trump tariff period lead to more heterogeneous and region-specific responses. Volatility transmission is shaped not only by financial globalization but also by the nature of each shock and the underlying structure of each market. These results offer important insights for international investors, policymakers, and risk managers, particularly regarding diversification, crisis response, and the design of resilient financial systems.

Keywords: Contagion, COVID-19, the Russia-Ukraine War, Trade Wars, E-GARCH, DCC-MGARCH

JEL: G01, G15, C52

I. Introduction

The frequency of financial crises in recent years has led many to conclude that financial markets are extremely sensitive to vacillations. Moderate vacillations that primarily influence only one industry disseminate to others and contaminate neighbouring industries. When the spillover effect is strong enough, considerable variations in one financial market will have fundamental effects on foreign markets. In extreme cases, joint movements of distinct financial markets cause the crisis to pass from region to region and grow into a contagion. The financial literature distinguishes between two types of contagion: pure contagion and fundamentals-based contagion (Calvo et. al., 1996, Masson 1998; Wolf, 1999; Forbes et. al., 2002; Dornbusch et. al., 2000). Pure contagion is also characterized as a psychological contagion and is frequently induced by the irrational behavior of self-fulfilling investors. Irrational human actions such as loss aversion, herd mentality, mental accounting, heuristic simplification, and panics can lead to market inefficiencies. Masson (1998) argues that even moderate shifts can lead to loss of confidence and higher perceived risk in holding certain financial instruments. According to Dornbusch et. al.,(2000), the market inefficiencies can be divided into liquidity constraints, information asymmetry, and adverse market equilibria. Contagious behavior among market participants causes shocks to spill over from one country to the next.

Fundamental-based contagion can be interpreted as shocks of a global or local nature that can spread across markets because of macroeconomic connections and financial interlinkages among countries. This fundamental connectiveness transform into contagion and have negative repercussions, especially when they take place during a period of crisis. Contagion effects based on fundamentals have been frequently observed in global financial markets in recent years. According to Stiglitz (1998), emerging markets are more vulnerable to vacillations. This is also justified by the Mexican "tequila crisis" of 1994, the "Asian flu" of 1997, and the "Russian virus" of 1998, which spread rapidly to other regions by contagion in a short time. In particular,

the 1998 Asian crisis spread further to Latin America and Russia. The Asian crisis adversely affected asset prices in these countries and capital flows, caused significant financial instability, and jeopardized economic growth throughout the region. Chiang et. al., (2007) highlight the importance of a longer-run outcome triggered by the crisis and its spillover effect, which forfeits the confidence of investors who had intended to invest in Asian and Latin American markets. According to the authors, investors' concerns can last for a long time and cause lasting damage to portfolio investments until another successful story of economic growth develops in the region. King and Wadhwani (1990) investigate the failure of market mechanisms in particular countries in the October 1987 stock market crash. The market collapse raised many questions about why markets around the world fell simultaneously and with surprising uniformity, even though they differed significantly in their economic outlooks and market structures.

King et.al., (1990) identify that the serial correlation in New York, Tokyo, and London returns is larger during the crash week and that contagion coefficients are an increasing function of actual and perceived volatility. Baig et.al., (1999) state that if the increase in correlation coefficients is significantly higher than the correlations during the 'tranquil' period, it indicates a shift in sentiment. They define contagion as a magnification in cross-market linkages during turbulent periods. If the join-movement does not magnify during the crisis, then uninterrupted high level of market correlation implies strong cross-market linkages that normally exist. Forbes and Rigobon (2002) use the term interdependence to refer to this condition. The authors state that contagion occurs only when the joint movements of two markets increase significantly after the vacillation. Following that, financial markets reflect current and future economic activity. In this paper, we use this correlation framework, which previous researchers have focused on, to study contagion. Using daily data, we measure contagion using the excessive co-movement crisis-based methodology.

In order to conduct an in-depth analysis, to build a good-fitting model, and to increase its predictive power, extensive researchers focus on the characteristics of financial asset returns. The returns of financial assets are usually characterized by time-varying correlations and do not fit the positive definite conditional variance matrix. The empirical applications developed under the appealing assumptions of constant correlations and the positive-definite conditional-variance matrix often inhibit the optimization of the log-likelihood function and lead to errors in the estimates. Additionally, financial time series tend to exhibit excessive kurtosis and negative skewness in the unconditional distribution. In addition, return series often exhibit problems with heteroskedasticity, which are exacerbated as price volatility increases. Mandelbrot (1963) confirms that even for very large and stationary sample sizes, the tails of stock price distributions can be so long that the second moments of the sample change unboundedly and erratically. Abhyankar (1995 & 1997) shows the process of generating financial return data as a nonlinear process. Nonlinearities in financial time series may emerge from swings in the business cycles as well as abrupt changes in economic, political, or policy regimes. It is, therefore, necessary to use a statistical method that smooths sharp political and economic transitions. On the other hand, this estimation method may be able to capture the dynamics, trends, and seasonality of the return data and provide solid approximations to the empirical models. In the academic literature, time series nonlinearities are explained in terms of conditional mean models of Threshold Autoregressive (TAR) developed by Tong (1977). If the nonlinearity in return series is the result of a changing conditional variance, such return series are estimated using the Autoregressive Conditional Heteroskedasticity and Generalised Autoregressive Conditional Heteroskedasticity models introduced by Engle (1982) and Bollerslev (1986). Bollerslev (1990) emphasizes that conditional correlation should be considered in addition to conditional variance in multivariate GARCH models. In this regard, Bollerslev introduced the CCC-GARCH model, a multivariate GARCH model, by introducing

the "Constant Conditional Correlations" (CCC) parameterization. Instead of the conditional correlation parameter used in CCC-GARCH models, Tse et.al., (2002) and Engle (2002) developed the DCC-GARCH model by using the "Dynamic Conditional Correlations" (DCC) parameterization.

Empirical applications of nonlinear structures that forecast price changes in terms of a changing conditional variance are numerous (Aloui et al., 2011; Kenourgios, & Samitas, 2011; Chouliaras et al., 2012; Bekaert et al., 2014; Kenourgios & Dimitriou, 2014; Alexakis et al., 2016; Echaust 2021; Elsayed et al., 2021). A major drawback of these models is that they are represented by the univariate case of the vectorized conditional-variance matrix, which follows the conventional autoregressive moving average return series analogue. In accordance with Tse & Tsui (2002) this formulation is very general and calls for further restrictions. Another major concern during the optimization of the log-likelihood function is maintaining the positive definite value of the conditional-variance matrix. To overcome these difficulties, constant correlation models have been developed to capture the maximum likelihood estimate of the correlation matrix is equal to the sample correlation matrix (Bollerslev, 1990). Angela Ng (2000) state that Bollerslev's traditional autoregressive moving average representation only approximates the characteristics of return time series, as correlation coefficients between stock markets are incredibly volatile over time. In this study we begin with the EGARCH method to examine volatility spillovers among major stock markets and we conduct an additional analysis with the DCC-GARCH technique to test for contagion effects. By tracking the time-varying correlation matrix, using the DCC-GARCH we can track time-varying regional market correlations, which allows us to observe whether there has been substantial transmission of stress and how continuous they are. We also capture market responses to extremely bad events that lead to excessive volatility and allowing us to identify markets that are more seriously contaminated.

The paper is organized as follows. The first section provides theoretical discussion. The second section outlines the data and methodology. The third section shows the empirical findings. Section four provides discussion and section five concludes.

2. Theoretical Discussion

Volatility transmission and cross-market contagion have been widely examined in the financial economics literature, particularly during periods of global stress. Early studies demonstrate that financial markets tend to become more correlated during crises, reducing diversification opportunities and amplifying systemic risk. (Forbes et.al. 2002). Some fundamental studies report that the pattern of contagion is uneven across time and regions with increased variability and joint movement occurring predominantly during times of crisis. (Baig and Goldfajn, 1999; Kaminsky and Schmukler, 1999; Connolly and Wang, 2000, Çelik 2012). Franses & Van Dijk (1996) use the QGARCH model to describe negative skewness in stock market indices, and highlight that the model is the best as the model sample does not contain extreme data such as the 1987 stock market crash. Bae et. al., (2003) find evidence of cross-regional contagion and report that contagion varies across regions and appears to be stronger within Latin America than it is within Asia. The authors report that the United States appeared to be completely isolated from any contagion from Asia during the 1997 Asian crisis. Azimova (2022) analyzes volatility spillovers among five Asian stock markets and their sector indices using a multivariate EGARCH model, revealing significant non-normality, volatility clustering, and asymmetric effects in most markets. The results show strong and bilateral volatility transmission in Hong Kong, South Korea, Malaysia, and Thailand, while Singapore remains relatively isolated with low comovement, offering greater diversification potential. Studies consistently document high integration within the euro area, especially between Germany and

France, reflecting deep financial and trade linkages (Baele et al., 2004; Härdle et al., 2015). This integration tends to persist across crisis and non-crisis periods. Emerging markets, on the other hand, show more variable volatility transmission, with spillovers often determined by commodity exposure, capital flow sensitivity, and domestic macroeconomic conditions (Bekaert et al., 2017; Morales et al., 2017). Chiang et al., (2007) analyze the correlation-coefficient series and distinguish two phases of the Asian crisis. The first is contagion, characterized by an increase in correlation. The second is the herding behavior, which shows a persistently high correlation. However, much of the increased pattern of volatility and comovement across countries remains unexplained. Some studies attribute the increased correlation between countries to globalization and integration of stock markets (Allen and Gale 2000; Van Rijkeghem and Weder, 2000; Laguna and Schrixt 2001). Other studies link this fact to the fact that financial markets respond to the same innovations and events. (Rigobon, 1998, Baig and Goldfajn, 1999; Kaminsky and Schmukler, 1999; Connolly and Wang, 2000). However, Kodres et al., (2002) provide evidence of time series and cross-sectional patterns of contagion in financial markets and report that contagion can occur even in the absence of public news and between countries that do not directly share the same generic macroeconomic channels. This implies that shocks between two countries can be transmitted indirectly by a third country. Another branch of the academic literature emphasizes contagion from currency crises and links it to various financial and monetary vulnerabilities, including but not limited to financial market inadequacies, weaknesses in government policies, and incomplete contracting. (Agenor et al., 1998, Chan-Lau and Chen 1998, Corsetti, Pesenti, and Roubini 1999, Kaminsky and Reinhart 2000). To rule out additional distributional mechanisms, Franklin et al. (2000) exclude the effects of international foreign exchange markets in the propagation of financial crises from one country to another.

To determine the pattern of contagion in financial markets, some studies refer to a set of formal channels for contagion, including channels for correlated liquidity shocks, correlations between asset returns, and correlated information. According to Yuan (2005), under the correlated liquidity shock channel, the liquidation of assets to obtain cash takes place in a number of markets, leading to the transmission of shocks. King and Wadhvani (1990) refer to the correlated information channel as the tendency of markets to respond to price changes in other markets, causing their prices to change as well. Kodres and Pritsker (2002) assert another important transmission channel is the extent of information asymmetry in different markets and the degree to which they interact. A higher degree of interaction increases the contagion effect. Some studies assume that market participants have complete information about the markets, as incomplete information can provide another channel for contagion.

COVID-19 had become a new type of risk for investors worldwide leading to weaker external demand and illiquid financial markets. Following the outbreak of the pandemic in recent months, countries came under financial and macroeconomic stress, leading to deteriorating financial conditions and excessive volatility in global equity markets. Recent investigations by the International Monetary Fund (IMF) accentuate that “the magnitude and speed of collapse is unlike anything experienced in a lifetime”. Find estimates that global economic output has declined threefold and that the cumulative output loss from the pandemic crisis could reach \$9 trillion by the end of 2021 (IMF 2021). The number of studies confirming the negative economic impact of COVID-19 has increased rapidly (Alam et al., 2020; Baker et al., 2020; Khan et al., 2020; Corbet et al.,; Alshammari et al., 2020). However, evidence of financial contagion during the pandemic crisis using both constant and time-varying conditional correlations is sparse, but results to date from models with constant correlations are promising. Le and Tran (2021) conclude the existence of financial contagion from the U.S. stock market to the Vietnamese and Philippine stock markets. In particular, the Philippines appear to be more

affected by the contagion effect and the authors attribute this to differences in crisis management. Akhtaruzzaman et al.,(2021) explore how financial contagion occurs through listed firms in China and G7 countries during the COVID–19 period. The empirical results show that stock returns experience a significant increase in conditional correlations.

Similarly, geopolitical crises such as the Russia–Ukraine war have been found to increase global risk aversion and intensify cross-market contagion, especially in energy-dependent and emerging markets (Bialkowski et al., 2023; Umar et al., 2023). The Russia-Ukraine War, which began on February 22, 2022, created significant uncertainties that affected financial markets and led to considerable volatility. Western economies responded by quickly imposing economic and financial sanctions on Russia. Immediately following the Russian invasion, the Russian ruble lost 20.7% of its value against the US dollar in foreign exchange markets in a single trading day (February 28, 2022) (Santorsola et al., 2022). Russia's invasion exacerbated uncertainty and had created negative impacts on many sectors of the global economy, including trade, financial markets, agriculture, and other areas. An important issue during the war was the increase in natural gas and oil prices in global markets due to concerns about potential supply shortages in energy markets. The economic importance of crude oil and its ongoing connection to many other financial and commodity markets mean that the war, although directly affecting only two countries, had a global impact on financial markets and investor behavior (Adekoya et al., 2022, Kantar et.al., 2025). As investors reacted to Russia's invasion of Ukraine, stock markets experienced significant declines. In the first week after the invasion, the S&P 500 saw its first correction since the start of the COVID-19 pandemic. The link between global financial markets during the Russia-Ukraine war is associated with high levels of return and volatility spillovers as well as elevated geopolitical risk (Wang et al., 2022). Salisu et al. 2022 report that the geopolitical uncertainties (e.g., military buildups, war, and terrorism threats) have more negative effects on stock returns than geopolitical events). With the onset of the war, global stock markets exhibited negative cumulative abnormal returns with significant heterogeneous effects (Boubaker et al., 2022). Negative stock returns were observed in the capital markets of G20 countries (Yousaf et al., 2022) and in the capital markets of 94 countries worldwide (Boungou et al., 2022). Among the 25 EU stock market indices, markets geographically closer to the war zone and those with less efficient markets were more affected by this conflict (Kumari et al., 2023). Companies with greater liquidity performed better during the war-related crisis, while companies in European Union countries or those with high trade dependence on Russia reacted more negatively (Sun et.al., 2023). These findings suggest that extreme global shocks tend to produce broad-based volatility spillovers across both advanced and emerging markets.

As economic uncertainty increases, firms may reduce trade volume, avoid new investments, and implement changes to global production chains. Thus, the volatility caused by trade policies is not limited to import and export figures but extends across a broad economic spectrum (Handley et al., 2017). The effects of such policies are not limited to short-term price changes, but also affect investment decisions, production processes, and long-term economic growth (Irwin, 2017). Increases in trade policy uncertainty reduce investment at the firm and macroeconomic level. News of future tariffs and increased uncertainty are leading to lower investment and slowing economic activity. (Caldara et al., 2020). Trade wars are disrupting global supply chains (Amiti et al., 2019), reduces the possibility of firms entering new foreign markets (Crowley et al., 2018). The most productive firms are more affected by industry-wide spending fluctuations than less productive firms (De Sousa et al., 2020). One of the most significant impacts of trade policies is their pressure on volatility. Market expectations about the future lead to greater fluctuations in uncertain environments, undermining investor confidence (Fajgelbaum et al., 2020). The most significant events that have caused the greatest

damage to today's economic system and called it into question are the trade wars in international trade that began with the election of Trump as President in the United States in 2017, the main architect of this system. In fact, the intense protectionist trade policies initiated by the US during this period also indicate that the US is no longer as eager as before to maintain this leadership role within the liberal system under its hegemonic power. This process evokes a return to the protectionist policies within the liberal system experienced in international trade in the 1970s. Trump's foreign and trade policies during his first term are also seen as a response to the shortcomings of neoliberal globalization and internationalization experienced between 1990 and 2017 (O'Brian, 2024). Trump, in his second term, argues that free trade is not the case in practice and that in many cases, foreign governments use high tariffs, trade barriers, and intellectual property theft to harm U.S. economic and security interests. Trump's policies, which will negatively impact global trade, continue to escalate. This situation creates uncertainty in trade and financial markets. In contrast, trade-policy shocks often generate more heterogeneous market responses. The literature on the Trump tariff measures shows that the effects differ across countries depending on their exposure to global value chains, import/export dependence, and geopolitical alignment (Amiti et al., 2019). Tariffs imposed on China had substantial real and financial impacts on Chinese firms, yet global spillovers were uneven, with some markets becoming more connected while others diverged (Fang et al., 2022; Huang et al., 2020). China's partial capital controls, unique market microstructure, and high state ownership have also been identified as factors limiting cross-market integration and dampening volatility transmission from foreign shocks (Fernald et al., 2019; Yu & Hassan, 2022).

This paper is most closely related to studies of contagion among stock markets through the fundamentals-based contagion using the crisis-contingent methodology of excessively correlated shock channels in the age of political, geopolitical, trade, and COVID-19 uncertainties. That is, we define contagion as excessive correlation and emphasize that contagion occurs only when the intraregional correlation of two markets increases significantly during the crisis. Also, this study contributes to the finance literature by focusing on modeling the volatility of daily global price indices with two models, DCC-MGARCH and E-GARCH models over a longer time period that includes the pandemic and its aftermath. We apply a dynamic DCC-GARCH mechanism to capture all possible channels of transmission across stock markets. The definition of the dynamic DCC-GARCH model means that we effectively comment on country-specific, regional, and global fundamentals, as well as the structure that converts fundamentals into correlation. These models allow us to observe how market participants respond to shocks by rapidly reallocating their portfolios, how these adjustments transmit volatility across markets, and how such transmission evolves into measurable contagion effects.

3. Data and Methodology

3.1. Data

This paper investigates the presence of financial contagion in stock markets during periods of uncertainty, specifically the COVID-19 pandemic, the Russia-Ukraine War, and the second Trump tariff period, both across the entire period (December 16, 2019-July 31, 2025) and within specified sub-periods. The dataset uses stock returns as the primary proxies for aggregate economic activity in developed countries-the USA, Japan, Germany, and France and developing countries- Indonesia, Brazil, India, China, Turkiye and Russia. To ensure comparability across countries, we use daily returns per domestic stock index. The sample period covers December 16, 2019, to July 31, 2025. To compare and understand the impact of uncertainties on the sample stock markets, we divide the entire period into three sub-periods: the pandemic (December 16, 2019-May 12, 2021), the Ukraine-Russia War (February 22, 2022-

August 3, 2022, when the impact on oil prices normalized), and the second Trump tariff period (January 20, 2025-July 31, 2025). Demonstrating both the relationship between stock markets across all periods (contagion) and the relationship between stock market returns within the specified sub- periods will address a significant gap in the literature. In particular, the positive and negative divergence in stock market returns across these sub-periods will serve as a reference for policymakers and investors in their current or potential decisions. Figure 1 shows the closing values of the stock exchanges included in the study for the period from 16 December 2019 to 31 July 2025.

The figure shows the closing value of each index used in the study.

The daily time series involves 10 countries and 1.856 observations. Narayan et al. (2016) state that outputs of the statistical models are data frequency dependant. We use a daily data as the daily frequency captures most of the business-related cyclical profiles, provides a sufficient number of observations and therefore has a higher predicting ability. The price data is obtained using Data Stream. We further recalculate the asset prices into returns using the following formula: $R_t = \ln \left(\frac{P_t - P_{t-1}}{P_{t-1}} \right)$. By transforming the asset prices into returns, we venture to abate non-stationarity and heteroscedasticity problems and harmonize the variability of mean and variance.

Table 1 Variables

Abbreviation	Variable
S&P500	Standards and Poors 500 - USA
NIKKEI225	Tokyo Stock Market Exchange - Japan
DAX	Deutscher Aktienindex- Germany
CAC40	Cotation Assistée en Continu- France
MOEX	The Moscow Exchange Russia Index
NIFTY50	Indian Stock Market Index-India
JSCI	Jakarta Stock Market Index - Indonesia
BIST100	Borsa Istanbul 100 Return Index - Turkey
SSEC	Shanghai Composite Stock Exchange - China
BOVESPA	Bolsa de Valores de São Paulo - Brazil

3.2. Methodology

The heteroscedastic nature of the return time series exhibits non-constant conditional variances as well as time-varying conditional correlations as opposed to the constant-correlation model developed by Bollerslev (1990). The parameterization proposed by Bollerslev (1990) represents a condition in which the maximum likelihood estimate of the correlation matrix come up to the sample correlation matrix.

We apply the EGARCH method to examine volatility spillovers among major stock markets. The EGARCH model, developed by Nelson in 1991, is an asymmetric model based on the premise that positive and negative news have different effects on the volatility of financial assets, depending on market perceptions. This model assumes that the error terms follow the generalized error distribution. The EGARCH model accounts for asymmetric relationships and enables the identification of the ‘leverage effect’. The leverage effect describes the phenomenon where unfavorable news in the market causes greater volatility in financial assets than positive news. The main advantage of the EGARCH model over the GARCH model is its direct compliance with non-negativity constraints, as it uses the logarithm of the variance. This model is particularly favored by investors because it provides insight into

the leverage effect of a financial asset. If a negative correlation exists between returns and volatility, γ may be negative, indicating that the model captures asymmetry. (Brooks, 2008). EGARCH model is given below:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (1)$$

The analytic technique underlying this study is the varying-correlation MGARCH methodology developed by Tsui et al., in 2002. This methodology allows for time-varying correlations and yet retains the appealing feature of the conditional-variance matrix to be positive definite in the process of optimization of the log-likelihood function as defined by Engle et al. (1984).

$$\text{VAR}(y_t | C_{t-1}) = \Omega_t \quad (2)$$

C_{t-1} is the set of information at t and y_t is the correlation matrix.

MGARCH application follows the intuition of the univariate GARCH formulation, but yet supports time varying nature of each conditional-variance term in a vech-diagonal structure:

$$\sigma_{it}^2 = \omega_i + \sum_{h=1}^p \alpha_{ih} \sigma_{i,t-h}^2 + \sum_{h=1}^q \beta_{ih} \gamma_{i,t-h}^2, \quad i = 1, \dots, K, \quad (3)$$

ω_i , α_{ih} , and β_{ih} are nonnegative and $\sum_{h=1}^p \alpha_{ih} + \sum_{h=1}^q \beta_{ih} < 1$ for $i = 1, \dots, K$

In addition, a MGARCH model retains autoregressive moving average type analog and allows for the time-invariant conditional-correlation matrix τ_t .

$$\tau_t = (1 - \lambda_1 - \lambda_2)\tau + \lambda_1 \tau_{t-1} + \lambda_2 \varphi_{t-1} \quad (4)$$

$(1 - \lambda_1 - \lambda_2)$ is the time-invariant conditional correlation coefficient, it is assumed that $\lambda_1 > 0$ and $\lambda_2 > 0$ with $\lambda_1 + \lambda_2 \leq 1$. τ_t is the weighted average of τ and τ_{t-1} . φ_{t-1} is positive definite correlation matrix with unit diagonal elements which depend on the lagged values of standardized residuals ϵ_t as follows:

$$\varphi_{t-1} = \frac{\sum_{h=1}^M \epsilon_{i,t-h} \epsilon_{j,t-h}}{(\sum_{h=1}^M \epsilon_{i,t-h}^2)(\sum_{h=1}^M \epsilon_{j,t-h}^2)}, \quad 1 \leq i < j \leq K \quad (5)$$

$$\varphi_{t-1} = C_{t-1}^{-1} A_{t-1} A_{t-1}' C_{t-1}^{-1}$$

C_{t-1}^{-1} is the $K \times K$ diagonal matrix where the i th diagonal term is $(\sum_{h=1}^M \epsilon_{i,t-h}^2)^{1/2}$. A_{t-1} is the $K \times N$ matrix given by $(\epsilon_{t-1}, \dots, \epsilon_{t-N})$.

4. Empirical Findings

We first assess the statistical characteristics of the series of the selected sample group and provide the descriptive results in the pandemic, war and Trump tariff periods in Tables 2, 3, 4 and 5.

Table 2 16 December 2019-31 July 2025 (All Data)

Variable	Obs	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
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S&P500	1855	0.0453	1.2499	-12.7652	9.0894	-0.6368	18.2922
NIKKEI 225	1855	0.0318	1.2905	-13.2340	9.7365	-0.4377	14.6652
DAX	1855	0.0341	1.2262	-13.0548	10.4142	-0.7312	16.5222
CAC40	1855	0.0028	1.8350	-19.4906	15.3537	-2.0003	32.5503
NIFTY50	1855	0.0450	1.0829	-13.9038	8.4002	-1.4891	26.2808
SSEC	1855	0.0144	1.0577	-8.0392	7.7550	-0.5201	11.5259
JSCI	1855	0.0118	0.9964	-8.2318	9.6788	-0.4082	14.5117
BOVESPA	1855	0.0301	1.5013	-15.9930	13.0222	-1.4735	25.0871
BIST100	1855	0.1284	1.6908	-10.3068	9.4219	-0.7412	8.1128
MOEX	1855	0.0093	1.6994	-40.4670	18.2619	-7.0067	185.9013

Table 3 16 December 2019 – 05 May 2023 (Covid Period)

Variable	Obs	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
S&P500	884	0.0302	1.5222	-12.7652	8.9683	-0.7639	14.9351
NIKKEI 225	884	0.0219	1.2829	-6.2735	7.7313	0.0755	6.7147
DAX	884	0.0229	1.4947	-13.0548	10.4142	-0.7314	14.7963
CAC40	884	0.0268	1.4668	-13.0983	8.0560	-1.0593	14.8986
NIFTY50	884	0.0488	1.3176	-13.9037	8.4003	-1.7283	23.7444
SSEC	884	0.0151	1.0472	-8.0391	5.5542	-0.8414	9.6305
JSCI	884	0.0103	1.0972	-6.8051	9.6788	-0.0757	14.6410
BOVESPA	884	-0.0102	1.8728	-15.9930	13.0222	-1.5474	21.1800
BIST100	884	0.1563	1.7900	-10.3068	9.4219	-1.0193	9.3138
MOEX	884	-0.0187	2.1790	-40.4669	18.2619	-7.0203	143.5032

Table 4 22 February 2022 – 03 August 2022 (Ukraine-Russia War Period)

Variable	Obs	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
S&P500	117	-0.0389	1.5937	-4.1233	3.0105	-0.3530	2.8859
NIKKEI 225	117	0.0259	1.3082	-3.0537	3.8604	0.0878	3.1360
DAX	117	-0.0690	1.7112	-4.5083	7.6231	0.4727	5.7930
CAC40	117	-0.0407	1.6546	-5.0928	6.8827	0.3031	5.3430
NIFTY50	117	0.0143	1.2217	-4.8960	2.8481	-0.5053	4.4376
SSEC	117	-0.0231	1.3529	-5.2679	3.4245	-0.8757	5.4427
JSCI	117	0.0404	0.9479	-4.5155	2.2169	-1.2910	7.5360
BOVESPA	117	-0.0630	1.1867	-2.9433	2.3961	-0.3498	2.8274
BIST100	117	0.2354	1.5912	-8.5198	5.3128	-1.4571	10.6820
MOEX	117	-0.3056	4.5805	-40.4669	18.2619	-5.2210	53.9557

Table 5 20 January 2025 – 31 July 2025 (Trump Tariff Period)

Variable	Obs	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
S&P500	116	0.0269	1.5296	-6.1609	9.0894	0.8408	15.1007
NIKKEI 225	116	0.0409	1.7028	-8.1502	8.7354	0.2094	13.0499
DAX	116	0.0605	1.3877	-5.0799	4.4340	-0.3363	5.3679
CAC40	116	-0.2976	5.6999	-19.4906	15.3537	-0.7806	4.9834
NIFTY50	116	0.0663	0.8719	-3.2970	3.7472	0.3396	6.4654
SSEC	116	0.0552	0.9140	-7.6274	1.7949	-5.1383	44.4561
JSCI	116	0.0833	1.4460	-8.2318	4.6815	-1.4579	12.6000
BOVESPA	116	0.0381	0.9221	-3.0069	3.0702	0.2088	4.1672
BIST100	116	0.0824	1.8295	-9.1237	5.6193	-1.3201	10.8916

MOEX	116	-0.1551	1.4874	-3.5474	4.1960	0.0513	3.0146
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In Table 2, we observe that the mean of stock market returns are positive. During the pandemic period (Table 3), the mean values are mostly positive except for the Brazilian and Russian Stock Exchanges. In Table 3, we notice that Brazil, Türkiye and Russia display the most fluctuations. Apparently, the stock data for most economies are negatively skewed and exhibit fat tails. During the COVID period, negative skewness is largest in Russia, suggesting that the magnitude of negative returns is more dominant. The positive skewness in the return series of Japan during the COVID period indicates a fat tail on the right and the presence of asymmetry in this equity market.

During the Ukraine-Russia War, negative skewness is again largest in Russia, suggesting that negative returns are more dominant. Positive skewness is observed in the return series for Japan, as well as Germany and France. During the Trump Tariff Period, negative skewness diminishes with the negative largest skewness found in China. This result is expected, as the main target of Trump's tariffs was the Chinese economy. We see the positive skewness in the return series for the USA, Japan, India and Brazil.

A particularly notable parameter is the positive, increasing, and high value of kurtosis during the pandemic period with Russia, exhibiting the highest kurtosis. This suggests that, for the group of markets in the sample, large shocks of both signs are influential, stock returns obviously deviate from the normal distribution, and have thick tails. A leptokurtic distribution with heavy tails in stock data also implies that the index has a propensity for extreme outlier return values, increasing investment risk. The DCC-MGARCH model is adequate to capture the statistical features of stock returns that display non-normal properties.

Table 6 presents correlation coefficients between stock exchanges. The highest correlation between stock markets is between the S&P 500 and the DAX (0.96). The next highest correlations are between the S&P 500 and the Nikkei 225, and between Nikkei 225 and the DAX (0.94). The lowest correlation between exchanges is between MOEX and JSI (-0.05).

Table 6 Correlation Coefficients Between Stock Exchanges

Variables	S&P500	NIKKEI 225	SSEC	DAX	CAC40	MOEX	NIFTY50	JSCI	BIST100	BOVESPA
S&P500	1.00	0.94	0.44	0.96	0.91	0.47	0.93	0.70	0.90	0.85
NIKKEI_225	0.94	1.00	0.38	0.94	0.91	0.46	0.93	0.69	0.91	0.85
SHANGAI	0.44	0.38	1.00	0.42	0.27	0.48	0.29	0.05	0.28	0.33
DAX	0.96	0.94	0.42	1.00	0.94	0.48	0.92	0.64	0.88	0.84
CAC40	0.91	0.91	0.27	0.94	1.00	0.35	0.94	0.78	0.91	0.80
MOEX	0.47	0.46	0.48	0.48	0.35	1.00	0.27	0.05	0.23	0.52
NIFTY50	0.93	0.93	0.29	0.92	0.94	0.27	1.00	0.83	0.95	0.82
JSCI	0.70	0.69	0.05	0.64	0.78	0.05	0.83	1.00	0.80	0.61
BIST100	0.90	0.91	0.28	0.88	0.91	0.23	0.95	0.80	1.00	0.79
BOVESPA	0.85	0.85	0.33	0.84	0.80	0.52	0.82	0.61	0.79	1.00

Before continuing with the model estimations, we have applied the augmented Dickey-Fuller (ADF) and the Efficient Modified Phillips-Perron (PP) analysis to check the availability of unit root in time series. The estimation outputs demonstrate that all ADF and PP test statistics are significant at the 1% %5, %10 levels, thereby implying that stationarity is maintained for all stock return series (Table 7).

Table 7 ADF and PP Unit Root Tests Results for Stock Markets

Variable	ADF Unit Root Test		War Period	Trump Period	PP Unit Root Test		War Period	Trump Period
	All Period	COVID 19			All Period	COVID 19		
S&P500	-50.312***	-36.708***	-10.674***	-11.746***	-50.087***	-36.338***	-10.674***	-11.766***
NIKKEI 225	-45.327***	-29.211***	-10.200***	-14.197***	-45.281***	-29.262***	-10.200***	-13.872***
DAX	-44.477***	-30.897***	-11.201***	-11.317***	-44.485***	-30.901***	-11.225***	-11.301***
CAC40	-45.372***	-30.565***	-11.275***	-11.503***	-45.374***	-30.604***	-11.291***	-11.585***

NIIFTY50	-44.886***	-31.145***	-10.268***	-11.379***	-44.848***	-31.117***	-10.269***	-11.365***
SSEC	-43.681***	-29.971***	-9.991***	-11.377***	-43.677***	-29.984***	-10.209***	-11.578***
JSCI	-42.134***	-28.533***	-10.900***	-10.533***	-42.198***	-28.720***	-10.938***	-10.539***
BOVESPA	-50.123***	-36.190***	-9.065***	-10.077***	-49.681***	-35.670***	-9.042***	-10.102***
BIST100	-41.974***	-29.099***	-12.183***	-9.890***	-42.071***	-29.256***	-12.100***	-9.885***
MOEX	-40.688***	-28.111***	-10.243***	-10.222***	-40.623***	-28.077***	-10.434***	-10.257***

***, **, * represent significance at the %1, %5, %10 level of significance respectively.

According to Forbes & Rigobon (2002) presence of conditional heteroskedasticity in return time series will affect estimates of cross-market correlation coefficients. Analysis of return time series is further reinforced by investigating conditional heteroskedasticity. The estimations show that the ARCH-LM test is significant at 5 percent (Table 8).

Table 8 ARCH-LM Results

ALL	SP500	NIKKEI225	DAX	CAC40	NIFTY50	SSEC	JSCI	BOVESPA	BIST100	MOEX
lag4	407.341***	445.433***	225,129***	303,991***	270,186***	36,209***	212,822***	530,599***	94,018***	75,763***
lag8	479.458***	464,255***	356,466***	424,683***	399,130***	87,250***	297,697***	639,978***	106,251***	75,723***
lag12	479.150***	467,349***	398,528***	556,465***	462,878***	96,152***	311,476***	650,984***	110,140***	75,573***
COVID	SP500	NIKKEI225	DAX	CAC40	NIFTY50	SSEC	JSCI	BOVESPA	BIST100	MOEX
lag4	207.485***	180.211***	99.380***	147.564***	135.228***	13.931***	144.832***	218.484***	36.960***	29.520***
lag8	262.621***	221.000***	168.064***	167.770***	200.558***	20.474***	229.561***	269.890***	49.349***	29.419***
lag12	261.641***	240.412***	192.717***	193.560***	231.727***	28.136***	243.675***	277.373***	50.961***	29.295***
WAR	SP500	NIKKEI225	DAX	CAC40	NIFTY50	SSEC	JSCI	BOVESPA	BIST100	MOEX
lag4	5.428	17.095***	11.550**	18.378***	3.483	12.781**	8.490*	5.193	0.925	82.623***
lag8	10.464	18.569**	14.244*	20.994***	17.988**	13.960*	11.957	5.599	2.651	13.669*
lag12	14.764	21.837**	26.681***	17.925	12.856	14.642	13.961	11.297	5.770	14.990
TARIFF	SP500	NIKKEI225	DAX	CAC40	NIFTY50	SSEC	JSCI	BOVESPA	BIST100	MOEX
lag4	20.974***	26.198***	39.996***	5.216	4.159	0.053	3.304	15.726***	23.383***	12.276**
lag8	25.973***	31.566***	45.027***	10.415	7.465	0.138	3.605	19.887**	24.209***	16.640**
lag12	27.625***	32.700***	44.102***	17.731	8.116	0.242	5.275	23.029**	23.588**	20.994*

Chi²; ***, **, * represent significance at the %1, %5, %10 level respectively. H0: There are no ARCH effect on residuals.

The ARCH-LM test statistics for both models reject the null hypothesis and indicate on existence of ARCH effect in the residuals of return series (Figure 2).

The figure shows the actual and residual estimations of index series used in the study.

To check the existence of contagion, we employ EGARCH and DCC-MGARCH models. Table 9 summarizes the outputs of the EGARCH model for all period.

Table 9 Estimation Outputs of the E-GARCH for All Period

Variables	Prob	ϕ	μ	η	λ	θ
S&P500	0.0004	-0.263537	0.012771	0.239431	-0.044664	0.957996
NIKKEI225	0.0000	-0.122561	-0.001631	0.181473	-0.117457	0.929657
SSEC	0.0054	-0.150089	-0.029675	0.205984	0.024794	0.947960
DAX	0.5784	-0.272280	0.012852	0.356529	0.007869	0.987370
CAC40	0.0027	-0.338724	-0.017792	0.444677	-0.048422	0.973090
MOEX	0.0000	-0.179257	0.014014	0.250304	-0.074459	0.984874
NIFTY50	0.0000	-0.190029	0.024629	0.235495	-0.079942	0.956687
JSCI	0.0000	-0.098702	-0.028001	0.126496	-0.053032	0.981280
BIST100	0.0000	-0.134916	0.109308	-0.134916	-0.073338	0.899764
BOVESPA	0.0000	-0.109740	0.005637	0.147454	-0.047883	0.982902

In the EGARCH model, all markets except DAX are statistically significant, and for stock markets excluding SSEC, the λ parameters have negative coefficient, suggesting an asymmetric effect in the series. The negative value of this parameter indicates a leverage effect, meaning that negative shocks increase volatility more than positive ones. In other words, negative news impacts stock markets' volatility more than positive news. The θ parameters are high, indicating

a dense volatility cluster in the series. Table 10 summarizes the EGARCH's computational output for COVID-19 period.

Table 10 Estimation Outputs of the E-GARCH for COVID-19 Period

Variables	Prob	ϕ	μ	η	λ	θ
S&P500	0.0865	-0.379915	0.015791	0.328827	-0.044071	0.926775
NIKKEI225	0.0000	-0.082610	-0.029556	0.121012	-0.096870	0.959819
SSEC	0.0026	-0.144506	-0.037851	0.192654	-0.060148	0.903890
DAX	0.6959	-0.348861	-0.018158	0.446413	0.011753	0.972098
CAC40	0.5357	-0.41244	0.002296	0.511633	-0.018176	0.963374
MOEX	0.0000	-0.213728	0.057223	0.326208	-0.102477	0.970394
NIFTY50	0.0000	-0.120854	0.033611	0.152494	-0.159073	0.961601
JSCI	0.0000	-0.211558	0.026616	0.255004	-0.091995	0.913909
BIST100	0.0000	-0.154932	0.173690	0.348895	-0.078278	0.891362
BOVESPA	0.0060	-0.098114	-0.010325	0.150840	-0.044291	0.965622

In the EGARCH model for the COVID-19 period, all markets except DAX, S&P 500 and CAC 40 are statistically significant. The λ parameters for the stock markets have negative coefficient, suggesting an asymmetric effect in the series. This negative parameter indicates on the leverage effect, meaning that negative shocks increase volatility more than positive ones. In other words, negative news impacts stock markets' volatility more than positive news. The θ parameters are again high, indicating a strong volatility clustering in the series. Table 11 summarizes the EGARCH computational output for the Russia-Ukraine war period.

Table 11 Estimation Outputs of the E-GARCH for the Russian-Ukraine War Period

Variables	Prob	ϕ	μ	η	λ	θ
S&P500	0.0410	-0.453753	-0.023454	-0.041683	-0.315106	0.769639
NIKKEI225	0.0501	-0.026799	-0.017784	0.014334	-0.192694	1.024606
SSEC	0.0011	-0.141725	-0.119682	0.247818	-0.266504	0.910598
DAX	0.3447	-1.031049	-0.013151	0.898163	-0.149010	0.760214
CAC40	0.3802	-1.048115	-0.036230	0.984341	0.144262	0.842528
MOEX	0.0000	1.228925	-0.319538	0.946098	0.649977	-0.710478
NIFTY50	0.0515	-0.088426	0.092250	0.077109	-0.264473	0.873115
JSCI	0.1937	0.092822	0.074129	-0.143794	-0.122562	0.074129
BIST100	0.0000	0.820372	0.414305	-0.651667	-1.051707	-0.007242
BOVESPA	0.0454	-1.104147	-0.030131	0.543144	0.329913	-0.874126

In the EGARCH model for the Russia-Ukraine war, all markets except DAX, CAC40, and JSCI are statistically significant. During this period, the CAC40 and JSCI stock exchanges, along with the DAX, are not significant. The λ parameters for the stock markets have negative coefficient, suggesting an asymmetric effect in the series. The θ parameters are also high.

Table 12 summarizes the EGARCH's computational output for the Trump Tariff period.

Table 12 Estimation Outputs of the E-GARCH For the Trump Tariff Period

Variables	Prob	ϕ	μ	η	λ	θ
S&P500	0.0048	0.048686	0.030646	-0.149611	-0.159556	0.969387
NIKKEI225	0.0892	0.222753	-0.035240	-0.169727	0.332371	0.030891
SSEC	0.0007	-0.427340	0.141895	-0.427340	0.493221	0.800229
DAX	0.0695	-1.391455	0.112656	1.326860	-0.371349	-0.069398
CAC40	0.0060	-0.063790	0.021261	0.277939	0.301310	0.970973
MOEX	0.1360	-0.057700	-0.197558	0.269683	-0.251001	0.720970
NIFTY50	0.0423	-0.545721	-0.062595	0.623585	-0.227256	0.873493
JSCI	0.0000	-0.303569	0.139853	0.476208	-1.611466	0.766371
BIST100	0.0000	0.564917	0.166570	-0.329551	-0.772126	0.504734
BOVESPA	0.1421	0.164851	0.059691	-0.590984	0.260452	0.451226

In the EGARCH model for the Trump Tariff period, all markets except NIKKEI225, DAX, MOEX and BOVESPA are statistically significant. During this period, the NIKKEI225, MOEX and BOVESPA stock exchanges accompany the DAX, are not significant. The λ parameters except for SSEC, have a negative coefficient, suggesting an asymmetric effect in the series. The θ parameters are also high for specified indexes. The positive value of this parameter for SSEC indicates that the asset has no leverage effect. Table 13 summarizes the computational output of the DCC-MGARCH for all period and 3 sub-periods.

Table 13. Estimation Outputs of the DCC-MGARCH

DCC-MGARCH MODEL													
		ALL Period			COVID-19 period			Ukraine-Russia War Period			Trump Tariff Period		
		Constant (ω)	$\alpha (\varepsilon_{t-j}^{(2)})$	$\beta(h_{t-j})$	Constant (ω)	$\alpha (\varepsilon_{t-j}^{(2)})$	$\beta(h_{t-j})$	Constant (ω)	$\alpha (\varepsilon_{t-j}^{(2)})$	$\beta(h_{t-j})$	Constant (ω)	$\alpha (\varepsilon_{t-j}^{(2)})$	$\beta(h_{t-j})$
Developed Markets	S&P500	0.043112***	0.132914***	0.838836***	0.072616***	0.127778***	0.829061***	0.2308052	0.099881*	0.808349***	-0.003128	0.171062***	0.849396***
	NIKKEI 225	0.197794***	0.144364***	0.731199***	0.085876**	0.071439***	0.871848***	2.032315	0.297167***	-0.497993	0.712669*	0.301270**	0.320152
	DAX	0.030868***	0.094715***	0.889744***	0.052410***	0.082512***	0.887024***	0.006131	0.065395***	0.930702***	0.575992*	0.262620	0.343451*
	CAC40	0.315913***	0.103748***	0.887297***	0.060679***	0.080786***	0.880776***	-0.020068	0.051491**	0.951799***	0.846909	0.365511*	0.684100**
Emerging Markets	MOEX	0.012867**	0.139278***	0.876686***	0.035633**	0.179756***	0.846296***	1.518855***	2.648418***	0.259568***	0.553524	0.178035*	0.577275**
	NITY50	0.039152***	0.126229***	0.842422***	0.032973***	0.112165***	0.870514***	2.462194***	0.068001*	-0.807219***	0.175187*	0.181561	0.605866**
	SSEC	0.062193***	0.084617***	0.866296***	0.050656***	0.068391***	0.890731***	0.5845028**	0.276971**	0.407271**	2.211939***	-0.007769***	-0.998475***
	JSCI	0.024049***	0.076328***	0.902034***	0.108731***	0.146201***	0.744006***	1.770856	0.053575***	-0.933001	0.995452**	0.099747	0.420241*
	BOVESPA	0.030527***	0.061039***	0.914196***	0.133388***	0.061049***	0.879061***	2.262666	-0.179148***	-0.401454	1.655192***	0.1231255***	-0.986752***
	BIST100	0.162990***	0.087528***	0.860523***	0.150272***	0.086954***	0.870084***	5.843933***	0.054347***	-0.998780***	4.884010***	-0.004772	-0.977536***

***, **, * %1, %5, %10 level of significance.

The results in Table 13 highlight that the ARCH and GARCH coefficients for the period are statistically significant and their sums meet the condition of being less than 1. All ARCH and GARCH coefficients are statistically significant, during the COVID-19 period, and their sums meet the condition of being less than 1. In the Ukraine-Russia War time-grid, even though the coefficients of the JSCI and BOVESPA variables are statistically insignificant, their sums remain less than 1. In the final the Trump tariff sub-period, although the GARCH coefficient of the NIKKEI 225 variable and the ARCH coefficient of the BIST100 variable are statistically insignificant, the sums of the ARCH and GARCH coefficients still meet the condition of being less than 1.

Stock markets in both developed and developing countries are among the most important indicators of a country's economic performance. Thus, whether the stock market returns of these countries are affected by the returns of other countries-in other words, whether there is a contagion effect between the stock market returns of these countries-remains an important consideration in the finance literature. Table 14 highlights the findings of the dynamic conditional correlation coefficients of the country stock market returns obtained with the DCC-MGARCH model.

Table 14 Estimation Outputs of the Dynamic Conditional Correlation Coefficients (DCC-MGARCH)

DCC-MGARCH													
		ALL PERIOD			COVID Period			Ukraine-Russia War Period			Trump Tariff Period		
		Corelation Coefficient	Z Test	Prob.	Corelation Coefficient	Z Test	Prob.	Corelation Coefficient	Z Test	Probability	Corelation Coefficient	Z Test	Prob.
S&P500	NIKKEI 225	0.1436	2.85	0.004	0.1444	1.94	0.053	0.2489	3.01	0.003	0.2428	2.64	0.008
	DAX	0.4095	9.45	0.000	0.4269	6.65	0.000	0.5600	9.30	0.000	0.3317	3.94	0.000
	CAC40	0.3516	7.84	0.000	0.4321	6.84	0.000	0.5381	8.64	0.000	-0.1587	-1.61	0.108
	BIST100	0.1557	3.15	0.002	0.0899	1.23	0.218	0.1733	1.76	0.078	0.1111	1.33	0.183
	BOVESPA	0.3743	8.49	0.000	0.4302	6.94	0.000	0.6450	13.16	0.000	0.3542	4.08	0.000
	NIFTY50	0.2351	4.82	0.000	0.3216	4.68	0.000	0.4265	5.76	0.000	0.1735	1.85	0.064
	SSEC	0.1000	1.94	0.052	0.0539	0.69	0.491	0.0376	0.41	0.683	0.1288	1.25	0.212
	JSCI	0.1321	2.63	0.009	0.1735	2.34	0.019	0.1364	1.46	0.146	0.0734	0.78	0.438
	MOEX	0.1876	3.83	0.000	0.2118	2.99	0.003	0.0895	0.98	0.327	0.0668	0.70	0.482
NIKKEI 225	DAX	0.2025	4.01	0.000	0.1252	1.63	0.103	0.2657	3.23	0.001	0.5122	7.04	0.000
	CAC40	0.1724	3.41	0.001	0.1357	1.79	0.074	0.3104	3.90	0.000	0.0975	0.94	0.348
	BIST100	0.0506	1.01	0.314	0.0254	0.35	0.728	0.1925	2.05	0.040	0.1738	2.10	0.036
	BOVESPA	0.1165	2.31	0.021	0.1173	1.54	0.123	0.2212	2.61	0.009	0.2817	3.06	0.002
	NIFTY50	0.1397	2.79	0.005	0.0847	1.11	0.268	-0.0036	-0.04	0.967	0.3492	4.12	0.000
	SSEC	0.1889	3.79	0.000	0.2447	3.35	0.001	0.2204	2.60	0.009	0.4925	5.89	0.000
	JSCI	0.1957	4.04	0.000	0.2635	3.73	0.000	0.4231	5.93	0.000	0.1359	1.38	0.166
	MOEX	0.1152	2.31	0.021	0.1342	1.84	0.066	0.0270	0.30	0.763	0.2514	2.77	0.006
DAX	CAC40	0.8359	47.29	0.000	0.8964	50.68	0.000	0.9360	76.94	0.000	0.0197	0.18	0.856
	BIST100	0.1881	3.80	0.000	0.1589	2.19	0.029	0.4802	5.87	0.000	0.2492	3.17	0.002
	BOVESPA	0.2376	4.80	0.000	0.2736	3.76	0.000	0.4888	7.33	0.000	0.1595	1.66	0.096
	NIFTY50	0.1513	2.95	0.003	0.1419	1.83	0.068	0.2585	3.06	0.002	0.2142	2.32	0.020
	SHANGAI	0.0816	1.55	0.121	0.0353	0.44	0.658	0.0767	0.83	0.409	0.2913	3.03	0.002
	JSCI	0.1195	2.34	0.019	0.0976	1.27	0.204	0.1428	1.53	0.126	0.1453	1.54	0.124
	MOEX	0.1543	3.06	0.002	0.1453	1.95	0.051	0.0760	0.84	0.402	0.0087	0.09	0.928
CAC40	BIST100	0.1941	3.94	0.000	0.2091	2.94	0.003	0.4850	5.95	0.000	-0.1282	-1.52	0.128
	BOVESPA	0.2334	4.76	0.000	0.2603	3.58	0.000	0.4759	7.02	0.000	0.0486	0.49	0.624
	NIFTY50	0.1068	2.07	0.038	0.1049	1.35	0.176	0.2159	2.51	0.012	-0.0165	-0.17	0.865
	SSEC	0.0835	1.60	0.110	0.0377	0.48	0.634	0.0889	0.97	0.334	0.1184	1.08	0.281
	JSCI	0.1197	2.35	0.019	0.1228	1.62	0.105	0.1598	1.72	0.085	-0.0645	-0.67	0.502
	MOSCOW	0.1548	3.09	0.002	0.1478	2.01	0.044	0.0724	0.80	0.424	0.1290	1.34	0.179
BIST100	BOVESPA	0.0704	1.40	0.161	0.0503	0.68	0.494	0.1315	1.31	0.191	0.0601	0.70	0.486
	NIFTY50	0.0861	1.73	0.084	0.0013	0.02	0.986	0.0084	0.08	0.932	0.0892	1.06	0.289
	SSEC	0.0204	0.41	0.684	-0.0078	-0.11	0.915	0.0424	0.41	0.681	0.1858	2.12	0.034
	JSCI	0.0973	1.99	0.047	0.0857	1.19	0.233	0.1239	1.18	0.236	0.0888	1.06	0.287
	MOEX	0.0779	1.57	0.117	-0.0048	-0.07	0.946	0.0252	0.25	0.800	0.0894	1.07	0.285
BOVESPA	NIFTY50	0.1363	2.71	0.007	0.1709	2.26	0.024	0.2825	3.40	0.001	0.1267	1.31	0.191
	SSEC	0.0786	1.53	0.125	0.0621	0.79	0.430	0.1414	1.54	0.123	0.1301	1.17	0.242

	JSCI	0.1061	2.09	0.036	0.1142	1.48	0.138	0.0996	1.04	0.297	0.1454	1.46	0.143
	MOEX	0.1279	2.58	0.010	0.1353	1.87	0.062	0.0920	1.01	0.315	0.1595	1.66	0.097
NIFTY50	SSEC	0.1052	2.08	0.038	0.0761	0.97	0.331	-0.1416	-1.59	0.111	0.4023	4.50	0.000
	JSCI	0.0912	1.81	0.071	0.1135	1.49	0.137	-0.0108	-0.11	0.910	0.0665	0.69	0.488
	MOEX	0.1226	2.48	0.013	0.2299	3.29	0.001	0.3585	4.32	0.000	0.0570	0.59	0.554
SHANGAI	JSCI	0.1174	2.31	0.021	0.2073	2.75	0.006	0.1011	1.06	0.289	-0.0394	-0.36	0.717
	MOEX	0.0652	1.30	0.192	0.066	0.89	0.371	-0.055	-0.06	0.952	0.1978	1.97	0.049
INDO	MOEX	0.0727	1.47	0.142	0.0843	1.16	0.245	0.0467	0.49	0.624	-0.0695	-0.74	0.460

***, **, * %1, %5, %10 level of significance.

Over all periods (December 16, 2019-July 31, 2025), the highest correlation, or contagion effect, of the S&P 500 index, which represents the US stock market and developed country stock markets that best reflect global capital markets, is with the German (DAX) and Brazilian (BOVESPA) stock markets at 40.95% and 37.43%, respectively. The lowest correlation is with Chinese (SSEC) stock market at 10.00%. For the relationship between the return of the Nikkei 225 index, the highest correlation is with the DAX at 20.25%, followed by the JSCI (Indonesian stock market) at 19.57% and the lowest correlation is with the BIST 100 (Turkish stock market) at 5.06%. Among stock exchanges, the highest correlation between the DAX index return, selected as a proxy for the German stock market, is with the CAC40 (French Stock Exchange) at 83.59% and the S&P500 variable (US Stock Exchange) at 40.95%, while the lowest contagion is observed with the SSEC at 8.16%. For the CAC40 index return, selected as a proxy for the French stock market, the highest correlation is with the DAX at 83.59%, and the S&P500 variable at 35.16%, while the lowest contagion is with the SSEC at 8.35%.

The BIST 100 has the highest contagion effect with the CAC40 at 19.41% and the DAX at 18.81%, while the lowest contagion is with the SSEC at 2.04%. For the contagion effect of other developing country stock markets, the BOVESPA, representing the Brazilian stock market, shows the highest contagion effect at 37.43%, while the S&P 500 variable has the lowest contagion effect at 7.86%, consistent with other country stock markets. The NIFTY50 index return, representing the Indian stock market, has the highest contagion effect at 23.51%, while the S&P 500 variable has the lowest contagion at 9.12%. The SSEC index return, representing the Chinese stock market, has the highest contagion effect at 18.89%, while the NIKKEI 225 and BIST 100 variables both have the lowest at 2.04%. The JSCI index return, representing the Indonesian stock market, has the highest contagion effect at 19.57%, while the NIKKEI 225 variable has the highest contagion effect. The variable with the lowest contagion effect is the MOEX at 7.27%. The S&P 500 variable has the highest contagion effect on the return of the MOEX, representing the Russian stock market, at 18.76%, while the SSEC has the lowest contagion effect at 6.52%.

During the COVID-19 period (December 16, 2019 - May 5, 2023), the highest contagion effect for the S&P 500 index is with the CAC40 variable at 43.21% and the BOVESPA at 43.02%. The lowest correlation is with the SSEC at 5.39%. For the NIKKEI225 index, the highest correlation is with the JSCI with 26.35% and the SSEC at 24.47%. The lowest correlation is the BIST 100 at 2.54%. For the return of the DAX index, the CAC40 shows a significant at 89.64%. The S&P 500 has the lowest correlation with the DAX, at 42.69%, while the SSEC has the lowest correlation, at 3.53%. The highest correlation for CAC40 index returns is with the DAX at 89.64%, followed by the S&P 500 at 43.21%, and the lowest with the SSEC at 3.77%.

The BIST 100 has the highest contagion with the CAC40 at 20.91%, the DAX at 15.89%, and the lowest with SSEC at -0.78%. The BOVESPA index shows the highest contagion effect at 43.02%, while the S&P 500 index and BIST 100 both have the lowest at 5.03%. The NIFTY50 has the highest contagion effect at 32.16%, followed by the S&P 500 index at 22.99%, and the BIST 100 index at 0.01%. The SSEC has the highest contagion effect at

24.47%, followed by the NIKKEI 225 and JSCI, both at 20.73%. The BIST 100 index has the lowest contagion effect at -0.78%. The JSCI index has the highest contagion effect on the return, with the NIKKEI 225 at 26.35% and the SSEC at 20.73%. The MOEX has the lowest contagion effect, at 8.43%. The MOEX has the highest contagion effect on the return, with the NIFTY at 22.99% and the S&P 500 at 21.18%. The BIST 100 had the lowest contagion effect, at -0.048%.

During the Ukraine-Russia War period (February 22, 2022 - August 3, 2022), the highest correlation, or contagion effect, of the S&P 500 index return is with the BOVESPA at 64.50% followed by the DAX at 56.00%, respectively. The lowest correlation is with the SSEC at 3.76%. For the NIKKEI225, the highest correlation is with the JSCI at 42.31% followed by the CAC40 at 31.04%, secondly. The least correlation is with the NIFTY50 with -0.036%. For the DAX, the highest correlation is with the CAC40 at 93.60%. The S&P 500 has a correlation of 56.00%, while the MOEX has the lowest correlation at 7.60%. The CAC40 has the highest correlation with the DAX at 93.60%, with the S&P 500 at 53.81%, and the lowest with the MOEX at 7.24%.

The BIST 100 shows the highest contagion with a 48.50% correlation, followed by the DAX at 48.02%, and the lowest with the NIFTY50 at 0.084%. The BOVESPA has the highest contagion effect at 64.50%, while the S&P 500 has the lowest at 8.20%. The MOEX shows the highest contagion effect at 42.65%, followed by the S&P 500 at 35.85%, and the lowest with the NIKKEI 225 at -0.013%. The SSEC return has the highest contagion effect at 22.04%, followed by the NIKKEI 225, and BOVESPA both at 14.14%, while the MOEX has the lowest contagion effect at -0.055%. The NIKKEI225 has the highest contagion effect at 42.31%. The NIFTY50 has the lowest contagion effect at -0.01%. The MOEX has the highest contagion effect at 35.85%. The SSEC has the lowest contagion effect at -0.055%. Despite Russia's increased economic relations and oil trade with China during the Russia-Ukraine war, there is no interaction between the two stock markets. During the same period, the correlation between the two stock markets increased significantly due to Russia's increased economic relations and oil trade with India.

During the Trump Tariff period (January 20, 2025 to July 31, 2025), the highest correlation, or contagion effect the S&P 500 index return is with the BOVESPA at 35.42% and the DAX at 33.17%. The lowest correlation is with the CAC40 at -15.87%. For the NIKKEI225 index return, the highest correlation is with the DAX at 51.22%, followed by the SSEC at 49.25%. The lowest correlation is with the CAC 40 at 9.75%. The French stock market diverged negatively due to the problematic Trump-Macron disputes and political conflicts. For the DAX index return, the S&P 500 has the highest correlation at 33.17%, respectively. The SSEC has the highest contagion rate at 29.13%, while the MOEX variable has the lowest at 0.087%. The highest correlation for CAC40 index returns with MOEX, at 12.90%, SSEC, at 11.84%, and the S&P 500, at -15.84%. Among developing countries, the BIST 100 has the highest contagion rate at 24.92%, followed by the DAX, at 18.58%, and the SSEC, at -12.82%. The lowest contagion rate is in the CAC40, at -12.82%. The BOVESPA has the highest contagion effect at 35.42%, while the S&P 500 has the lowest at 4.86%, and the CAC40 has the lowest at 40.14%. The NIFTY50 return shows the highest contagion effect at 40.14%, followed by the SSEC at 34.92%, and the CAC40 at -1.65%. The SSEC index return has the highest contagion effect at 49.25%, followed by the NIKKEI225 and DAX at 29.13% each. The variable with the lowest contagion effect is the JSCI at -3.94%. The JSCI return has the highest contagion effect at 14.53%, followed by the DAX. The lowest contagion effect is the MOEX at -6.95%. The NIKKEI225 has the highest contagion effect on the return of the MOEX at 25.14%. The variable with the lowest contagion effect is the JSCI at -6.95%.

5. Discussion

The results of the EGARCH estimations show that most stock markets in the sample exhibit significant volatility dynamics and asymmetric responses, across the full period and during the three major crisis episodes. The negative and statistically significant λ (leverage) parameters in most cases indicate that negative return shocks increase volatility more than positive shocks of the same magnitude. This asymmetric behavior is consistent with the well-known leverage effect documented in the literature (Black, 1976; Nelson, 1991) and suggests that investors react more strongly to adverse information, especially during periods of heightened uncertainty. During the COVID-19 period, almost all markets display statistically significant EGARCH parameters, except for the DAX and CAC 40. Markets that remain significant during this period also show negative λ values, indicating pronounced asymmetric volatility. This finding aligns with other studies suggesting that the health crisis notably increased risk and uncertainty within the global financial system. (Uddin et al., 2021; Basuony et.al., 2021). The insignificant statistics for the DAX and CAC 40 may reflect their stronger policy support measures, greater market depth, and faster information absorption, which can weaken the detectability of volatility asymmetry in shorter crisis windows. For the Russia-Ukraine war period, most markets again show significant EGARCH effects, except for the DAX, CAC 40, and JSCI. The significant markets continue to display negative λ values, indicating that geopolitical tensions intensified downside-driven volatility. This pattern is consistent with recent research showing that the Russia-Ukraine conflict increased global market uncertainty and volatility, especially in markets with higher energy dependence or direct regional exposure (Wu, 2023; Gheorghe, 2023). During the Trump tariff period, most indices remain statistically significant except for the NIKKEI 225, DAX, MOEX, and BOVESPA. For the significant markets, the λ coefficients are again negative, suggesting that trade-policy shocks primarily increased volatility through negative news, such as tariff announcements and trade restrictions. This finding aligns with evidence that tariff announcements generate sharp negative reactions and heightened volatility in globally integrated markets. (Amiti et al., 2019). Across all periods, the SSEC consistently does not display a negative and significant λ parameter. This indicates a more symmetric volatility response in the Chinese market. Prior studies attribute this pattern to the structure of the Chinese market, which is characterized by high retail participation, daily price limits, and frequent government interventions that can dampen the asymmetric volatility patterns typically observed in other markets (Chen et al., 2021). The DAX also stands out as an index that is frequently not statistically significant across all periods. This suggests that the German market exhibits relatively more stable volatility dynamics. This finding also reflects market structure characteristics, such as strong institutional participation and hedging mechanisms, which can reduce volatility asymmetry during crisis episodes.

The results of the DCC-MGARCH estimations reveal important patterns of interconnectedness among global stock markets over the full sample and across major crisis periods. Overall, the results show that contagion is not uniform across markets. Instead, it depends on the economic and financial integration of countries, geographical proximity, and the nature of each crisis. These findings are broadly consistent with the literature showing that global stock markets become more correlated during periods of stress, but that the strength of contagion varies by region and market structure (Engle, 2002; Kenourgios et al., 2015; Bouri et al., 2021).

Across the full sample, the S&P 500 exhibits the strongest correlations with the DAX and BOVESPA, suggesting that both Germany and Brazil are highly sensitive to developments in US equity markets. This finding aligns with evidence that the US remains the dominant transmitter of volatility and financial shocks to both developed and emerging markets (Diebold & Yilmaz, 2016). In contrast, the SSEC shows the weakest correlation with the S&P 500 and

most other markets, indicating low integration of China's equity market with global financial systems. Prior studies attribute this to capital controls, limited foreign participation, and structural differences in market regulation. (Chen et al., 2021; Huang et al., 2022).

The results for the COVID-19 period confirm a strong co-movement between major European markets. In particular, the DAX and CAC40 indices display correlations approaching 90%. This pattern supports earlier findings that European markets experienced strong contagion due to shared exposure to pandemic shocks, similar fiscal responses, and synchronized lockdown measures (Akhtaruzzaman et al., 2021). The S&P 500 also exhibits elevated correlations with both the CAC40 and BOVESPA during COVID-19, reflecting the global nature of the pandemic and increased global risk aversion. However, the Chinese market remains weakly connected, consistent with earlier research suggesting that China decoupled from global market volatility during early COVID-19 due to strict domestic controls and rapid recovery (Zhang et al., 2020). During the Russia–Ukraine war period, correlations intensify further among most markets. The S&P 500, DAX, CAC40, and BOVESPA show substantial increases in co-movement, reflecting heightened global uncertainty from geopolitical conflict. The core markets of Europe, DAX and CAC40, display exceptionally high correlations above 90%, reinforcing the idea that geopolitical proximity amplifies financial contagion (Wu, 2023). In contrast, correlations involving the SSEC, NIFTY50, or MOEX show more variation, reflecting differences in regional exposure, energy dependence, and domestic policy responses. (Gheorghe, 2023).

During the Trump Tariff period, the SSEC, representing China, showed relatively high correlation with some markets (e.g., Nikkei 225 at 49.25%) but negative or weak correlation with others (e.g., CAC 40 at −1.65%), reflecting the asymmetric impact of US tariffs on Chinese firms and sectors. Since China was the primary target of the US tariffs, its market experienced sector-specific pressures, trade uncertainty, and regulatory responses that led to heterogeneous transmission of shocks internationally. Additionally, the negligible correlation between the SSEC and S&P 500 during the Trump Tariff period suggests that, despite being the primary target of US trade measures, China's equity market remained largely decoupled from US market movements. This can be attributed to China's market segmentation, regulatory interventions, sector-specific effects of tariffs, and domestic investor behavior. Furthermore, during the Trump Tariff period, the correlation structure became more mixed. Some market pairs, such as S&P 500–BOVESPA and Nikkei 225–DAX, showed strong co-movement, indicating that trade policy uncertainty can increase global market integration, especially among economies with strong trade ties to the US (Amiti et al., 2019). However, several negative or very weak correlations also appeared, particularly involving the CAC 40 and SSEC, suggesting that trade-policy-driven shocks may cause divergence rather than convergence in some markets. (Fang et al., 2022).

Taken together, international equity markets display persistent and time-varying characteristics in both volatility and interconnectedness. Asymmetric volatility is common, especially during crisis periods, reflecting that negative shocks tend to increase market risk more than positive shocks. However, the presence and strength of this asymmetry depend on market structure and regulatory features, as shown by the SSEC, which consistently exhibits weaker responses. Contagion patterns indicate that extreme global events, such as the COVID-19 pandemic and the Russia–Ukraine war, produce the strongest co-movement across markets, while more policy-specific shocks, such as US tariffs, generate heterogeneous responses that vary by country. The Chinese market remains largely decoupled in all periods, highlighting the effects of market segmentation and domestic policy interventions, whereas European markets, particularly the DAX and CAC40, consistently show high co-movement due to deep financial integration. Emerging markets, including BOVESPA, JSCI, NIFTY50, BIST100, and MOEX,

exhibit intermediate and variable levels of connectedness, depending on the type of shock and their economic linkages. These results indicate that market contagion is shaped not only by the degree of financial globalization but also by the nature of the shock and the structural characteristics of each market. The high regional bilateral correlations that emerged in stock markets, particularly during the Trump era, illuminate the debate about whether globalization is shifting toward more regional patterns. Recent trade and currency wars, as well as regional military issues, are leading to the formation of new local alliances. These new alliances are reviving the phenomenon of regional localization rather than financial globalization. Geopolitical uncertainties, in particular, are bringing the Cold War era to mind. New regional developments, conflicts, and tensions in trade and finance are expected in the coming years. Therefore, periodically revisiting this topic will shed light on global transformation.

6. Conclusion

This study examines volatility dynamics and contagion among ten major global stock markets from December 2019 to July 2025, covering three significant crisis episodes: COVID-19, the Russia–Ukraine war, and the Trump tariff period. Using EGARCH and DCC-MGARCH models, the analysis reveals two key findings. First, asymmetric volatility is a persistent feature in most markets, with negative shocks having a stronger impact than positive shocks. However, the magnitude of this asymmetry depends on market structure and regulatory features, as seen in China’s SSEC. Second, the degree of contagion varies across markets and crises. Extreme global events, such as the pandemic and geopolitical conflict, cause strong co-movement across most markets, while policy-specific shocks, like tariffs, lead to heterogeneous responses, with some markets decoupling entirely. European markets show consistently high integration, emerging markets display intermediate and variable connectedness, and China remains largely segmented from global financial shocks.

These results have important implications for investors, policymakers, and risk managers. They indicate that diversification benefits are limited during global crises, especially among highly integrated markets, while segmented markets may offer partial hedging opportunities. Moreover, the findings underscore the need for dynamic risk assessment and stress-testing frameworks that account for time-varying volatility and correlation structures. The study confirms that both the nature of shocks and structural market characteristics play a critical role in shaping volatility transmission and market contagion.

Figure Legends

Figure 1 The stock Exchanges Closing Values

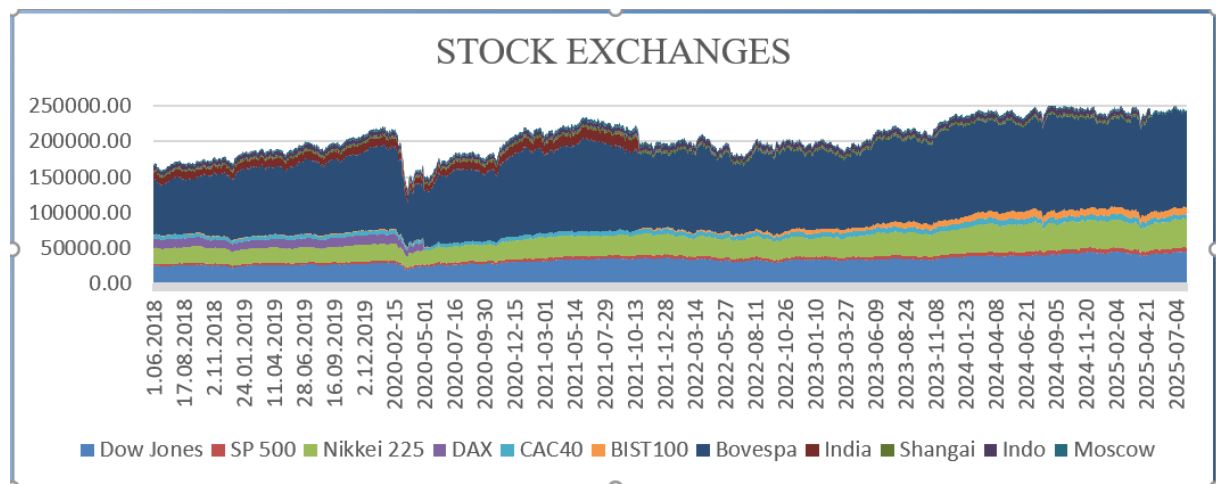
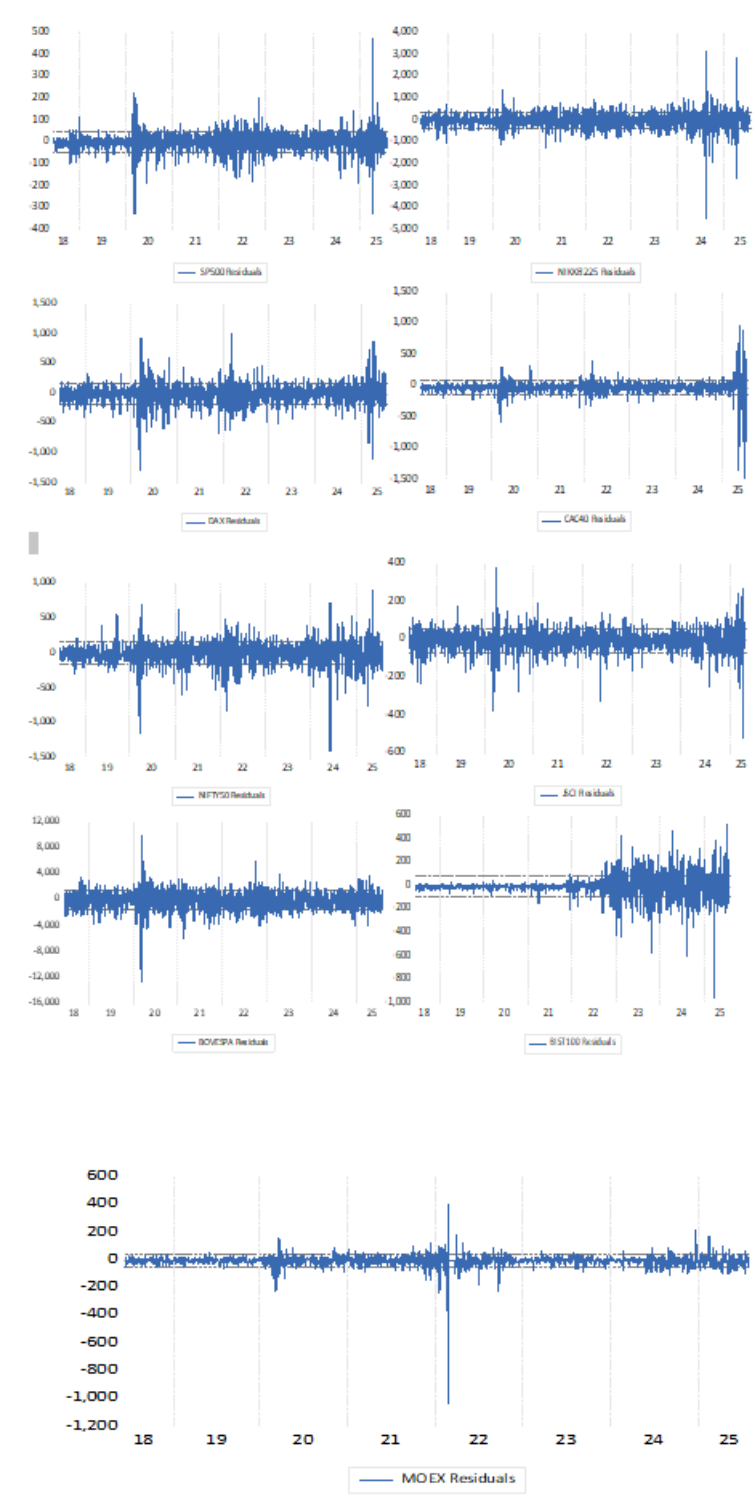


Figure 2 Actual and Residual Estimations of Index Series



Statements and Declarations

Ethical Approval: This article does not contain any studies with human participants performed by any of the authors.

Informed Consent: This article does not contain any studies with human participants performed by any of the authors.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRedit authorship contribution statement

Data availability

- 1.Raw Datasets Indexes
- 2-LNTransform All Data
- 3.Financial Contagion DCC_Garch All period
- 4.Financial Contagion DCC_Garch Covid period
5. Financial Contagion DCC_Garch War period
6. Financial Contagion DCC_Garch Trump period
7. Arch LM Formula
8. Arch LM Output
9. All Results _ Stata Packing Programming_DCC Garch
10. All Results _Eviews Packing Programming E-Garch

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