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VOLATILITY SPILLOVER EFFECTS BETWEEN STOCK MARKETS DURING THE CRISIS PERIODS: DIAGONAL BEKK APPROACH

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Abstract

A rise in the yield of financial market assets could lead to variations in the returns of other assets over time due to arbitrage conditions. Consequently, this phenomenon may trigger spillover effects or cointegration among the volatilities of assets within financial markets. The aim of this study is to investigate spillover effects among American, European, Russian, and Turkish stock markets during the COVID-19 pandemic and the Russia-Ukraine war. Employing the diagonal BEKK-GARCH model from 2020 to 2023, the volatility transmissions within stock returns is examined. The results reveal significant GARCH effects alongside modest ARCH effects. Notably, during the COVID-19 period, the European market exerted the most significant influence on other markets, whereas during the war period, the US market dominated, and Turkish markets displaying the least impact for two periods. Furthermore, the findings indicate that the lagged cross-volatility persistence is lower during the Russia-Ukraine war period compared to the COVID-19 period.

Keywords: *Volatility Spillover, Spillover Effect, Diagonal BEKK-GARCH, Turkish Stock Market, Global Stock Markets.*

KRİZ DÖNEMLERİNDE HİSSE SENEDİ PİYASALARI ARASINDA VOLATİLİTE YAYILMA ETKİLERİ: DIAGONAL BEKK MODELİ

Öz

Finansal piyasa varlıklarının getirisindeki bir artış, arbitraj koşulları nedeniyle zaman içinde diğer varlıkların getirilerinde değişikliklere yol açabilir. Sonuç olarak, bu olgu finansal piyasalardaki varlıkların volatiliteleri arasında oynaklık yayılma etkilerini veya eşbütünleşmeyi tetikleyebilir. Bu çalışmanın amacı, COVID-19 salgını ve Rusya-Ukrayna savaşı sırasında Amerika, Avrupa, Rusya ve Türkiye hisse senedi piyasaları arasındaki volatilite yayılımını araştırmaktır. Diagonal BEKK-GARCH modelini 2020'den 2023'e kadar uygulayarak, hisse senedi getirilerindeki volatilite aktarımları incelemektedir. Sonuçlar,kısmi ARCH etkilerinin yanı sıra belirgin GARCH etkilerini ortaya koymaktadır. Özellikle, COVID-19 döneminde Avrupa piyasası diğer piyasalar üzerinde en önemli etkiyi gösterirken, savaş döneminde ABD piyasası baskın olmuş ve Türkiye piyasaları iki dönem boyunca en az etkiyi göstermiştir. Ayrıca sonuçlar, Rusya-Ukrayna savaşı döneminde gecikmeli çapraz volatilite kalıcılığının COVID-19 dönemine kıyasla daha düşük olduğunu göstermektedir.

Anahtar kelimeler: *Volatilite Yayılımı, Yayılım Etkisi, Diagonal BEKK-GARCH, Türk Hisse Senedi Piyasası, Küresel Hisse Senedi Piyasaları.*

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1.INTRODUCTION

During the last two decades, technological advancements and the diversification of financial instruments in financial markets have resulted in a rapid response of financial instruments to new information, originating from both global and domestic markets. In finance literature, a rise in the return of a particular asset can trigger simultaneous changes in the returns of other assets, referred to as mean spillover. When fluctuations in returns begin, they require time to decelerate, leading to a phenomenon known as volatility spillover. Given that the behavior of financial instruments in markets significantly influences the decision-making processes of policymakers and economic agents, it becomes crucial to thoroughly examine and comprehend the spillover effects among the financial markets. Researchers have thoroughly examined the transmission of volatility between financial markets, particularly during periods of crises (Jude et al., 2023; Zhou et al., 2023).

In the past decade, the world has experienced various crises, with notable events including the global pandemic of COVID-19 and the ongoing Russia-Ukraine conflict. These crises have had significant impacts on economies and financial markets worldwide. For instance, COVID-19 has brought the global economy to a standstill, and the economic slowdown has led to sharp stock market declines, especially in the first year of the pandemic (Alaoui Mdaghri et al., 2021; Baruna, 2020). The US stock market triggered the circuit breaker mechanism four times within ten days, in March 2020. Alongside this crash in the US, stock markets in Europe and Asia also experienced significant declines (Zhang et al, 2020). On March 12, 2020, the UK's main index, the FTSE, decreased more than 10% in its worst single-day performance since 1987[1]. Similarly, Japan's stock market fell by over 20% from its December 2019 peak[2]. Investors' panicked behavior significantly increased the markets' volatility (Li et al., 2022). In addition, stocks of companies operating in the healthcare, technology, and e-commerce sectors rose during the pandemic, while the tourism, aviation, and retail sectors suffered heavy losses. Post-pandemic economic recovery and supply chain disruptions have led to higher inflation rates in Europe and many developing countries. The Ukraine-Russia war has not only caused a crisis in energy markets, causing oil and natural gas prices to rise rapidly, but also food prices (Astrov et al., 2021). This situation caused a decrease in the income of economies already under inflationary pressure and a slowdown in economic growth. Due to increasing pressures and political uncertainty, investors seeking safe havens withdrew from markets they found unsafe, and global market volatility increased again (Maurya et al., 2024).

During and following the global COVID-19 pandemic, the contagion effects among stock markets have notably intensified. Yousef (2020) investigated how the volatility of G7 indices was affected during this period. Their findings demonstrated that COVID-19 positively impacted conditional variance across all seven indices, leading to an escalation in market volatility. Similarly, Aslam et al. (2021) conducted a comprehensive examination of intraday volatility transmissions among twelve European stock exchanges. Their research revealed that a significant portion of intraday volatility forecast errors (77.80%) stemmed from transmissions, with Sweden and the Netherlands emerging prominently in this regard, while Poland and Ireland exhibited relatively lower levels. Additionally, Prasad et al. (2023) addressed the influence of global stock market volatility on Indian exchanges, scrutinizing changes during both pre-pandemic and post-pandemic periods. Their studies emphasized how stock returns from countries such as the United States, the United Kingdom, Russia, France, Canada, and Brazil exerted contagion effects on Indian markets.

During the Russia-Ukraine war, researchers have once again focused on studying volatility spillovers between financial markets. Anyikwa and Phiri (2023) estimated returns and volatility spillovers among African, developed, and emerging markets from 2020 to 2022. Their findings revealed that African and emerging markets were the primary net receivers during the Russia-Ukraine conflict. Furthermore, they acted as transmitters of systemic shocks during this period, with higher network connectedness observed compared to the COVID-19 variants announcements. Gheorghe and Panazan (2023) quantified the volatility resulting from the Russia-Ukraine conflict across 40 countries from January 1 to December 31, 2022. They observed anticipation of the conflict in markets near Ukraine, with a subsequent decline in volatility as war-related information emerged. Kumar and Koushik (2023) investigated the interdependence between the Russian Stock and Eastern European markets before and during the crisis, finding evidence of direct linkages in returns and volatility. Wu et al. (2023) proposed that the

1 https://www.bbc.com/news/business-51829852.
2 https://www.bloomberg.com/news/articles/2020-03-09/perfect-storm-is-plunging-asia-stocks-to-bear-markets-one-by-one.

effect of the Russia-Ukraine war on stock volatility from 2014 to 2022, finding an initial reduction followed by an increase in volatility after Russia's invasion of Ukraine.

This study investigates volatility spillover effects between American, European, Russian, and Turkish stock markets during different crisis periods. The research focuses on two main inquiries: firstly, examining whether there is contagion through volatility spillovers among American, European, Russian, and Turkish stock markets; secondly, assessing if there is a notable variation in volatility spillover between the periods of the COVID-19 pandemic and the Russian-Ukraine war. The problem of this study is to investigate whether volatility spillover effects exist in American, European, Russian, and Turkish stock markets during crisis periods. Global financial crises tend to increase market volatility, amplifying contagion effects across international markets. Since crises like the COVID-19 pandemic and the Russia-Ukraine war may have different effects, financial decision-makers and investors must understand how these crises affect volatility spillovers across markets. By comparing the volatility spillover effects of a health crisis such as the COVID-19 pandemic and a geopolitical crisis such as the Russia-Ukraine war, the study is expected to pave the way for understanding the effects of different types of crises on financial markets and developing more appropriate risk management strategies against crises.

Additionally, the volatility spillover between financial markets is a crucial topic for investors, portfolio managers, and policymakers; there is a lack of studies investigating the link between financial market volatilities, specifically within the context of the Turkish financial market. This research is expected to provide new insights into the behavior of the Turkish market during crisis periods. The study results will also be useful for financial authorities and regulators by helping better understand the risks of volatility spillovers across international markets. These contributions will allow for a better understanding of the linkages between financial markets, how volatility spillovers can be managed in times of crisis, and, in particular, to assess the international position of the Turkish financial market. Hence, this research employed the diagonal BEKK-GARCH methodology to examine and capture the transmission effects between the Turkish financial market (BIST 100) and three international financial markets.

The paper is organized as follows: The subsequent section delves into recent and pertinent research pertinent to the study. Section 3 elucidates the model design, while Section 4 presents an initial analysis. Section 5 deliberates on the empirical findings, and finally, Section 6 furnishes the conclusion of the study.

1.1.Conceptual and Theoretical Framework

Volatility refers to the fluctuation of rates of return on financial assets over time and is the statistical expression of the standard deviation or variance between returns. Volatility spillovers refer to the transmission of volatility from one market to another. Research on stock return volatility and its dispersion across markets began in the mid-20th century. Markowitz (1952) was the first to use risk, or volatility, as a mathematical concept in portfolio theory. In 1982, Robert F. Engle developed the ARCH (Autoregressive Conditional Heteroskedasticity) model and showed that volatility can be predicted not only from variables such as prices but also from historical volatility data. In 1986, Tim Bollerslev extended Engle's ARCH model and created the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. The GARCH model allowed for a better estimation of the volatility of financial assets. GARCH models are used to understand the volatility dynamics of financial markets.

Econometric methods that examine volatility spillovers can be generalized under two main modeling methodologies: Vector Autoregression (VAR) models and methods involving the use of ARCH and GARCH model families. Many studies in the literature use empirical tools such as VAR, cointegration, and variance analysis to analyze the volatility spillover effect between countries' stock markets (Belke and Dubova, 2018; Nandy and Chattopadhyay, 2019; Yılmaz, 2010). While VAR models address issues such as causality, the impact of shocks and the relationship between variables, GARCH models examine the dynamics of volatility in time series and volatility spillovers between different markets. Univariate GARCH models (ARCH, GARCH, EGARCH, etc.) are used to estimate the volatility of the prices of a stock or an asset (Li et al., 2016; Vo and Tran 2020). Multivariate GARCH models (BEKK-GARCH, Diagonal BEKK-GARCH, DCC-GARCH, etc.) are used to analyze the interrelationships and volatility dynamics of assets such as multiple stocks, currencies or indices (Sinlapates and Chancharat, 2024; Yousaf et al., 2024).

Moreover, in global financial systems, as markets become more integrated, fluctuations in one market can quickly spread to other markets in times of crisis (Diabold and Yılmaz, 2012; Koutmos and Booth, 1995; Zhang and Hamori, 2021; Wang et al., 2022). This study is built on the volatility spillovers during crisis periods, analyzing the impact of different crises on markets and understanding how these effects spread across markets.

2.LITERATURE REVIEW

Since the mid-20th century, the concept of volatility has been one of the most researched topics in the financial literature due to the development of technology and the widespread use of financial instruments. The concept of volatility spillovers, which refers to the effect of changes in volatility in one financial market or asset class on another market or asset class, is based on the idea that financial markets are interconnected and suggests that an increase in uncertainty or volatility in one market may lead to an increase in volatility in another market. There is a vast literature on spillover effects worldwide. Therefore, this study primarily focuses on research involving the Turkish stock market.

Extensive academic study has been devoted to examining the impacts of return and volatility spillover on stock prices across diverse global markets, employing various methodological approaches (Li et al., 2023; Tien and Hung, 2022; Yadav et al., 2023). These methods can generally be grouped under two main modeling methods. The cointegration and vector autoregression (VAR) models represent the first modeling methods. Many studies in the literature use empirical tools such as VAR, cointegration, and analysis of variance to analyze the volatility spillover effect across countries' stock markets. Eun and Shim (1989) used VAR analysis to analyze the dynamic responses of each of the nine global stock markets representing US, European, and Asia-Pacific markets to innovations in a particular stock market. The VAR model results show that the US stock market has a unidirectional price spillover effect on other stock markets. Using the VAR model, Liu (2016) investigated the spillover effect between the US, UK, Hong Kong, and Japanese stock markets. The VAR model results of the study on stock market returns between 2007 and 2009 revealed that the linkages between the East Asian market and the Japanese market with the global market strengthened in the post-crisis period, while the past performance of the US market did not affect market returns in the UK, Hong Kong, and Japan during the entire study period. Panda et al. (2019) used the Granger causality test, VAR model, vector error correction model (VECM) as the analysis method in their study in which they tried to analyze both the volatility spillover pattern between regional stock markets and the short and long-term interdependence between stock markets in the Africa and Middle East region. The results revealed that there is a significant spillover effect in the regional equity market, but the response amplitude and duration of the volatility spillover effect are very small.

Gürsoy and Eroğlu (2016) investigated the return and volatility transmission among Türkiye, Brazil, India, Indonesia, and South Africa, collectively referred to as the "fragile-five" countries, between 2006 and 2015. They employed the VAR-EGARCH model and found volatility spillover from India to the Turkish, Brazilian, Indonesian, and South African markets, as well as return volatilities from all four markets to the Indonesian stock market. Furthermore, following a volatility shock in Türkiye, it was identified that it counteracted the effects of unidirectional volatility in the Indian and Indonesian stock markets. Similarly, Bayramoğlu and Abasız (2017) used the VAR-EGARCH model to investigate volatility spillover in the MSCI Index from 2013 to 2016, analyzing the stock market indices of Brazil, Mexico, Russia, and Türkiye. Their findings indicate that negative shocks in the MSCI Index substantially influenced return variance more than positive shocks in the Mexican and Russian stock markets. Moreover, they noted symmetric but statistically insignificant volatility spillover effects between the Brazilian and Turkish stock markets. Liu et al. (2017) analyzed the transmission of volatility spillover among stock indexes of G20 countries from 2003 to 2015, utilizing the GARCH-BEKK model and VAR models. The BEKK model was applied across six sub-periods. The findings indicated a strong volatility spillover from Indonesia, Korea, and the US to the Turkish stock market from 2005 to 2006. Bozma and Basar (2018) studied volatility transmission among the Turkish, Ukrainian, Polish, and Hungarian stock markets from 2011 to 2016. Utilizing the VAR (1) BEKK-GARCH model for their estimations, they revealed that the BIST100 was influenced not only by its own volatility but also by volatility in the Polish and Hungarian stock markets. Bozma et al. (2023) endeavored to scrutinize volatility spillovers among Emerging and Growth-Leading Economies (EAGLE) stock market indices spanning from 2005 to 2019, employing a VAR model. Their investigation unearthed intriguing insights. Initially, they found that the total volatility spillover index stood at 10% in 2005, experiencing a substantial surge during the Global Financial Crisis (GFC), nearly tripling in magnitude. The heightened volatility spillover coincided with economic contractions in the Eurozone and the US debt crisis, culminating in a peak of approximately 40% before gradually subsiding until 2019. Among the EAGLE countries, Türkiye, Brazil, India, and Indonesia emerged as net receivers of volatility, indicating their susceptibility to external shocks. At the same time, Mexico, Russia, and China were identified as net transmitters of volatility, suggesting their role in propagating volatility across markets. Kocaarslan (2020) scrutinized the ramifications of the US stock market performance, Federal Reserve (FED) monetary policy, and US stock market uncertainty on the Turkish stock market. Employing both Autoregressive Distributed Lag (ARDL) and Nonlinear Autoregressive Distributed Lag (NARDL) models, the analysis delved into the intricate relationships among these variables. ARDL and NARDL models are regression models used in economics and finance to analyze dynamic relationships between variables and long-run cointegration. The study findings underscored that the volatility emanating from the US stock market exerted significant short and long-term effects on the Turkish stock market. Notably, these effects demonstrated asymmetry, particularly in the short term, highlighting the nuanced nature of inter-market dynamics.

The second modeling method can be defined as the use of ARCH and GARCH model families. Miyakoshi (2003), Nishimura and Men (2010), Kundu and Sarkar (2016), and Jebran et al. (2017) used the univariate variable ARCH and GARCH model families to investigate the spillover effect between different stock indexes. Karğın et al. (2018) explored the volatility spillover effects of the American, French, German, and stock markets on the BIST 100 index from January 2, 2004, to February 6, 2017, utilizing the E-GARCH (1,1) model. Their investigation uncovered that the volatility spillover effect on the BIST 100 index was not pronounced during periods characterized by moderate global risk. However, it was relatively higher during periods of elevated global risk. Yıldırım and Çelik (2020) conducted a comprehensive study exploring the impact of structural breaks on volatility persistence and asymmetry within the stock markets of twelve diverse countries, covering the period from 2013 to 2019. They meticulously analyzed market volatility dynamics by employing advanced econometric techniques, including GARCH and EGARCH models for volatility estimation and leveraging the ICSS iteration algorithm to pinpoint structural breaks. Notably, their findings revealed that among the countries under scrutiny, Türkiye, Russia, Indonesia, Brazil, and India stood out as the top five, characterized by enduring volatility patterns. Kutlu and Karakaya (2021) were keen on demonstrating the volatility and return transmission between the BIST and the Moscow Stock Exchange (RTS) spanning from 2005 to 2018 with the GARCH and the Aggregate Shock. Their findings indicated that investors in BIST considered both the returns and volatility of RTS, while those in RTS focused solely on the returns of BIST. Before the crisis, there was a one-way return transfer from BIST to RTS, with no reciprocal transfer. Conversely, post-crisis, no spillover was observed. However, mutual return and volatility spillovers occurred during the jet crisis between Russia and Türkiye.

However, in more recent research, multivariate GARCH models are more often employed (Aggarwal and Saradhi, 2024; Khan et al., 2023; Panda et al., 2021). The main reason is that univariate ARCH and GARCH model families cannot identify cross-effects and feedback effects between variables. In contracts, the multivariate GARCH models can identify the effects of cross-variable shocks and volatility transmission from other variables (Zhong and Liu, 2021). In their 2020 study, Alkan and Çiçek focused on investigating spillover effects between Turkish financial markets and analyzing the impact of global financial markets on the Turkish financial landscape. They observed that spillover effects could stem from both global and domestic financial markets. By employing the multivariate BEKK-GARCH model covering the period from 2006 to 2018, the study unveiled significant mean spillovers from global financial markets to both domestic stock and bond markets and from stock and exchange markets to the bond market.

In addition to ARCH/GARCH models, there are different many econometric models have been used in the literature, such as Switching Autoregressive Conditional Heteroskedasticity (SWARCH) and stochastic volatility modeling. The SWARCH model combines the volatility forecasting properties of ARCH or GARCH models with Markov regime switching properties. Özün and Ertuğrul (2014) utilized the SWARCH model to examine the causal relationship between the US stock market and European/emerging markets during the Global Financial Crisis (GFC) period from October 1, 2008, to September 4, 2009. Their findings revealed a one-way Granger causality from the Dow Jones to the UK, Germany, Russia, and Türkiye markets. Although the spillover of risk from the US markets to the Turkish ones is comparatively lower, it is stronger in the European markets. Akarsu (2022) used stochastic volatility modeling to investigate the interaction between BIST sector indices and the S&P 500 Index between 2012 and 2022. The study identified volatility transmission from the S&P 500 Index to the BIST Service Index and from the BIST Financial Index to the S&P 500 Index. During the COVID-19 pandemic, the study results revealed volatility transmission from all BIST sector indices to the S&P 500 Index and volatility spillover from the BIST Industry Index and BIST Financial Index to the US dollar/Turkish lira exchange rate. The results indicated increased volatility transmission among these financial markets following the pandemic.

Regardless of the analysis method, most of the studies in the literature have been conducted among developed countries, and there is believed to be a significant volatility spillover across these countries. (Ayadi and Said, 2023; Cheng et al., 2024; Jain and Sehgal, 2019; Lee and Rui, 2002; Liu et al., 2024; Gong et al. 2023; Mezghani et al., 2021; Tsuji, 2024; Pan et al., 2022; Zhang and Hamori, 2021). Zhong and Liu (2021) report that the US, UK, Japan, Germany, and France are among the markets where volatility transmission has been studied the most. Studies involving emerging markets mostly investigate volatility transmission from developed markets to emerging markets (Abounoori and Tour, 2019; Li, 2021; Li and Giles, 2015; Kırkulak Uludag and Khurshid, 2019; Mensi et al., 2021; Özdemir, 2020; Sahoo and Kumar, 2024; Yuan and Du, 2023). Moreover, the number of studies including Türkiye is more limited than those including other developed and developing countries. This study aims to contribute to this limitation by analyzing developed and emerging Turkish markets together during crises.

3.METHODOLOGY

The GARCH model was introduced by Bollerslev (1986) to improve the ARCH model based on its disadvantages. The GARCH model considers more past-period effects by incorporating a moving average structure into the ARCH model (Tsay, 2005; Özdemir, 2020). The error term of the GARCH model depends on past error terms and past conditional variance values. Accordingly, it considers the past error and conditional variance (Engle, 2001: 160).

The standard GARCH model can be articulated in the following manner.

$$H_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \cdots + \beta_p h_{t-p} \tag{1}$$

$$H_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{2}$$

The GARCH model outperforms the ARCH model by incorporating the moving average structure. However, volatility in the prices of markets and assets may spread to other markets or assets. The univariate GARCH model cannot detect such volatility analysis and spillovers.

The VECH GARCH model developed by Bollerslev et al. (1988) is known as the first multivariate GARCH model in the literature. The VECH GARCH model is calculated using Equation 3.

$$\begin{gathered} y_t = b + \delta H_i w_{t-1} + \varepsilon_t, \\ VECH(H_t) = C + \sum_{j=1}^{q} A_j \, vech(\varepsilon_{t-j}\varepsilon_{t-j}') + \sum_{j=1}^{p} B_j vech(H_{t-j}) \\ \varepsilon_t \mid \psi_{t-1} \sim N(0, H_4), \end{gathered} \tag{3}$$

Here it is;

C: Constant coefficient,

A_i and B_j: Matrices of coefficients.

The weakness of the VECH GARCH model is that it does not consider the dynamic linkages between financial time series by assuming that the variance and covariance values are positive (Tsay, 2005). Due to this limitation, this study does not apply the VECH GARCH model.

Engle and Kroner (1995) are credited with introducing the BEKK model, which is often seen as a constrained variant of the VECH model. The primary formula of the BEKK-GARCH model is presented in Equation 4.

$$H_t = C'C + \sum_{j=1}^{q}\sum_{k=1}^{k}(\alpha'_{kj}\,\alpha_{kj}\varepsilon_{t-j}\varepsilon'_{t-j})\sum_{j=1}^{p}\sum_{k=1}^{k}(\beta'_{kj}h_{qk,t-j}\beta_{kj}) \tag{4}$$

Where, C, α_{kj} and β_{kj} are $n\times n$ parameter matrix

Since the BEKK model is based on multi-matrix transposition, it requires a large number of calculations (Belasri, and Ellaia, 2017).

The diagonal BEKK model is similar to the BEKK model but is based on diagonal elements of the covariance matrix (diagonal). The diagonal BEKK parametrization models different elements of the covariance matrix depending on the past dependence levels between different variables. The model facilitates the consideration of correlations among covariance and contingent volatility. The number of parameters to be estimated in both the BEKK and diagonal BEKK analysis is provided in Equations 5 and 6.

$$p + q = KN^2 + (N(N + 1) / 2 \tag{5}$$

$$p + q = KN + (N(N + 1) / 2 \tag{6}$$

The BEKK interaction provides a framework for examining the transmission of volatility (Engle and Kroner, 1995). Additionally, the diagonal BEKK-GARCH model demonstrates robustness in estimation, stemming from its extension from the univariate GARCH model, which guarantees the semi-definiteness of the variance-covariance matrix. As a result, this model offers an advantage over previous models like VECH (Rastogi and Kanoujiya, 2024).

The variance–covariance matrix $H_{ij,t}$ is denoted as:

$$H_{ij,t} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \text{ for i, j =1or 2 at time (t)} \tag{7}$$

The volatility analysis of the two-asset BEKK GARCH model is explained by Equation 8:

$$H_t = C_0'C_0 + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} g_{11}^* & g_{12}^* \\ g_{21}^* & g_{21}^* \end{bmatrix}', H_{t-1} \begin{bmatrix} g_{11}^* & g_{12}^* \\ g_{21}^* & g_{22}^* \end{bmatrix} \tag{8}$$

The BEKK model defined in Equation (8) can also be expressed in its diagonal form by assuming that the matrices and g are diagonal. The matrix contains the parameters, with g denotes distinct volatility effects within its market and across markets. The parameters α_{11}, α_{22}, g_{11}, and g_{22} signify volatility effects within their respective markets, while α_{12},α_{12}, g_{12}, and g_{21} denote cross-market volatility effects.

Also, each conditional variance and covariance equation can be expressed as follows:

$$H_{11} = c_{11} + a_{11}^{*2}\varepsilon_1^2 + 2a_{11}^*a_{21}^*\varepsilon_1\varepsilon_2 + a_{21}^{*2}\varepsilon_2^2 \tag{9}$$

$$H_{12} = c_{12} + a_{11}^*a_{12}^*\varepsilon_1^2 + (a_{21}^*a_{12}^* + a_{11}^*a_{12}^*)\varepsilon_1\varepsilon_2 + a_{21}^*a_{22}^*\varepsilon_2^2 \tag{10}$$

$$H_{22} = c_{22} + a_{12}^{*2}\varepsilon_1^2 + 2a_{12}^*a_{22}^*\varepsilon_1\varepsilon_2 + a_{22}^{*2}\varepsilon_2^2 \tag{11}$$

This study utilizes a 4-variate Diagonal BEKK specification, wherein the conditional mean and variance-covariance estimates are obtained simultaneously through a system of four equations.

4.DATA AND PRELIMINARY ANALYSIS

The periods of global crises represent an unprecedented shock to financial markets. The primary objective of this research is to investigate the volatility spillover effects within American, European, Russian, and Turkish stock markets, namely S&P 500, STOXX 50, RTSI, and BIST 100. The S&P 500 index represents the 500 companies with the highest market capitalization in the US and is used as a proxy for the American stock market. The STOXX 50 index comprises top-tier companies from the Eurozone, recognized as industry frontrunners within their specific fields, and is used as a proxy for the European stock market. The RTSI Index comprises 50 Russian stocks listed on the Moscow Exchange, using a free-float capitalization-weighted methodology, with values denominated in US dollars, and is used as a proxy for the Russian stock market. Finally, the BIST 100 index is used as a proxy for the Turkish stock market. Table 1 represents the data description.

Table 1: Data description

Market	Acronym	Source
American stock market	S&P 500	www.investing.com
European stock market	STOXX 50	www.investing.com
Russian stock market	IRTS	www.investing.com
Turkish stock market	BIST 100	www.investing.com

The daily adjusted closing prices for all stock indices have been converted into daily log returns, representing the logarithmic changes in prices between two consecutive days, where R_{it} denotes log return at time t., P_t and P_{t-1} are the prices on two consecutive days.

$$R_i = log\left(\frac{P_{it}}{P_{t-1}}\right) * 100 \tag{12}$$

Figure 1 illustrates the daily logarithmic returns of the stock market from January 1, 2013, to December 31, 2023, focusing on individual stock markets. The volatility clustering in the daily logarithmic returns of stock market indices, denoted by significant ARCH effects, indicates the notable influence of both the COVID-19 pandemic and the Russia-Ukraine war on financial market indices. This observation motivates a closer examination of these effects, leading to the division of the analyzed periods into two segments: (1) the COVID-19 period spanning from February 2, 2020, to December 31, 2020; and (2) the Russia-Ukraine war period ranging from February 1, 2022, to December 31, 2023.

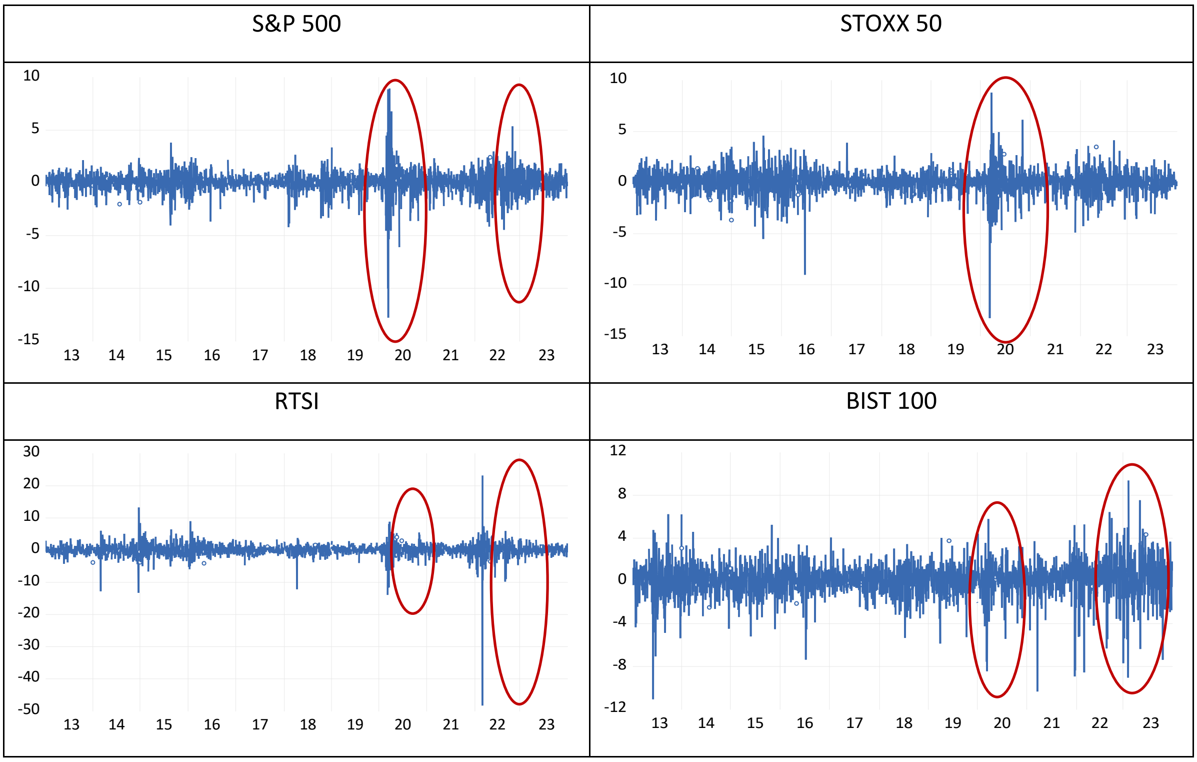


Figure 1: Stock Returns

Table 2 illustrates summary statistics of stock market returns for the COVID-19, and war periods.

Table 2: Summary statistics of stock markets

	COVID-19					WAR			
	S&P500	**STOXX50**	**RTSI**	**BIST100**		**S&P500**	**STOXX50**	**RTSI**	**BIST100**
Mean	0.117	0.026	-0.079	0.113		-0.010	0.018	-0.073	0.231
Max.	8.968	8.834	8.825	5.810		5.395	4.170	23.204	9.422
Min.	-12.765	-13.241	-13.949	-8.416		-4.420	-4.231	-48.292	-9.011
SD	2.269	2.083	2.729	1.715		1.213	1.132	3.344	2.145
Skewness	-0.762	-1.001	-1.197	-1.213		-0.065	-0.193	-6.140	-0.406
Kurtosis	11.129	11.746	8.850	7.743		4.288	4.480	103.584	5.677
JB	604.264*	711.056*	352.907*	250.707*		31.211*	43.558*	191,241.00*	145.781*
ADF	-20.937	-14.893	-14.652	-8.482		-20.717	-21.633	-8.817	-7.840
p-Value	0.000*	0.000*	0.000*	0.000*		0.000*	0.000*	0.000*	0.000*
Count	212	212	212	212		447	447	447	447

Note: ***, **, * denotes the significance level at 10%, 5 and 1% respectively. Unit Root Test is applied at constraint and trend.

During the COVID-19 period, the highest returns are observed in the US stock market, while the lowest returns are observed in the Russian stock market. Conversely, during the war period, the Russian stock market displays both the highest and lowest stock returns. Furthermore, the volatility of RTSI, represented by the standard deviation, is high (COVID-19: 2.729; War: 3.344), followed by S&P 500 (COVID-19: 2.269; War: 1.132), BIST 100 (COVID-19: 1.715, War: 2.145), and the volatility in STOXX 50 is lower (COVID-19: 2.083; War: 1.132). The standard deviation values clearly depict that all stock markets are highly volatile during both the COVID-19 and war periods. S&P 500, STOXX 50, RTSI, and BIST 100 indices have negative skewness coefficients and are left-skewed in both periods. On the other hand, all series have positive kurtosis coefficients and a peaked distribution. JB test results show that the data are not suitable for a normal distribution. The augmented Dickey–Fuller (ADF) test is the most common indicator for assessing the stationarity of a time series. Since the ADF test results shown in Table 2 are greater than the test critical values, it is concluded that the S&P 500, STOXX 50, RTSI, and BIST 100 indices are stationary. Accordingly, the null hypothesis (unit root) is rejected.

5.EMPIRICAL ANALYSIS

To explore the correlation between stock markets amid the COVID-19 pandemic and the Russia-Ukraine conflict periods, this study employs the estimation of a diagonal BEKK-GARCH model, as outlined in Table 3.

Table 3: Diagonal BEKK GARCH

	COVID-19						WAR			
	Coefficient	**Std.**	**T-Stat.**	**Prob.**			**Coefficient**	**Std.**	**T-Stat.**	**Prob.**
C(1,1)	0.1340	0.0607	2.2073	0.0273		C(1,1)	0.0179	0.0104	1.7254	0.0845
C(1,2)	0.0860	0.0397	2.1658	0.0303		C(1,2)	0.0207	0.0100	2.0621	0.0392
C(1,3)	0.0858	0.0418	2.0540	0.0400		C(1,3)	0.0206	0.0139	1.4834	0.1380
C(1,4)	0.0337	0.0370	0.9088	0.3635		C(1,4)	0.0103	0.0122	0.8439	0.3987
C(2,2)	0.0905	0.0383	2.3634	0.0181		C(2,2)	0.0489	0.0254	1.9223	0.0546
C(2,3)	0.1034	0.0432	2.3946	0.0166		C(2,3)	0.0097	0.0134	0.7254	0.4682
C(2,4)	0.1119	0.0530	2.1088	0.0350		C(2,4)	0.0227	0.0162	1.4055	0.1599
C(3,3)	0.2604	0.1129	2.3069	0.0211		C(3,3)	0.2345	0.0688	3.4102	0.0006
C(3,4)	0.1171	0.0662	1.7695	0.0768		C(3,4)	-0.0269	0.0269	-1.0005	0.3171
C(4,4)	0.3236	0.1328	2.4367	0.0148		C(4,4)	0.3591	0.1841	1.9502	0.0511
$\alpha_1(1,1)$	0.4064	0.0629	6.4653	0.0000		$\alpha_1(1,1)$	0.1748	0.0287	6.0985	0.0000
$\alpha_1(2,2)$	0.1665	0.0274	6.0779	0.0000		$\alpha_1(2,2)$	0.2139	0.0365	5.8547	0.0000

	COVID-19						WAR			
	Coefficient	**Std.**	**T-Stat.**	**Prob.**			**Coefficient**	**Std.**	**T-Stat.**	**Prob.**
α_1(3,3)	0.1963	0.0372	5.2774	0.0000		α_1(3,3)	0.3160	0.0376	8.4107	0.0000
α_1(4,4)	0.3516	0.0605	5.8139	0.0000		α_1(4,4)	0.2420	0.0488	4.9555	0.0000
B1(1,1)	0.8950	0.0273	32.8179	0.0000		B1(1,1)	0.9796	0.0065	149.8762	0.0000
B1(2,2)	0.9701	0.0089	109.4397	0.0000		B1(2,2)	0.9578	0.0156	61.5351	0.0000
B1(3,3)	0.9550	0.0162	58.7702	0.0000		B1(3,3)	0.9111	0.0168	54.2847	0.0000
B1(4,4)	0.8669	0.0423	20.4741	0.0000		B1(4,4)	0.9286	0.0294	31.6156	0.0000
AIC	14.1090					AIC	13.9760			
SC	14.4732					SC	14.1871			
HQ	14.2562					HQ	14.0592			
Note: S&P500 (1), Stoxx50 (2), RTSI (3), BIST100 (4)										

In Table (3), the c variables represent fixed parameters, α_i variables indicate the ARCH effect (the impact of short-term lagged shocks on the market), and βi variable represents the GARCH effect (long-term persistence). Positive coefficients observed in the off-diagonals of α_i imply that volatility tends to be more influenced when market downturns occur in synchrony rather than in opposite directions (Sajeev and Afjal, 2022). Notably, the statistically significant spillovers across all variables exhibit positive values, indicating a consistent directional impact. Furthermore, the analysis reveals that the ARCH and GARCH terms demonstrate significance levels below 5%, underscoring the substantial influence of the US stock market on the future volatility of STOXX50, RTSI, and BIST 100. These influences are stronger in the war period. The fact that β_i values of the model are higher than α_i values in both periods indicates that the GARCH effect is stronger than the ARCH effect. In other words, the multivariate volatility effect across markets is stronger than the volatility effect within each market, and this implies that during crises, market volatility persists over the long term, meaning that markets are unable to recover quickly from shocks. Moreover, positive β_i values indicate a positive conditional covariance effect across markets, as shown in Figure 2.

Accordingly, the results of the diagonal BEKK (1,1) model under Student-t distribution are summarised by the following equations (Table 4).

Table 4: Variance-covariance representation

COVID-19	WAR
$h_{11} = 0.133961 + 0.165134\varepsilon^2_{1,t-1} + 0.801094h_{11,t-1}$	$h_{11} = 0.017906 + 0.030558\varepsilon^2_{1,t-1} + 0.959550h_{11,t-1}$
$h_{12} = 0.085990 + 0.067660\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.868306h_{12,t-1}$	$h_{12} = 0.020714 + 0.037387\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.938182h_{12,t-1}$
$h_{13} = 0.085816 + 0.079768\varepsilon_{3,t-1} + 0.854733h_{13,t-1}$	$h_{13} = 0.020623 + 0.055239\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.892489h_{13,t-1}$
$h_{14} = 0.033653 + 0.142879\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.775876h_{14,t-1}$	$h_{14} = 0.010263 + 0.042295\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.909642h_{14,t-1}$
$h_{22} = 0.090507 + 0.027722\varepsilon^2_{2,t-1} + 0.941157h_{22,t-1}$	$h_{22} = 0.048910 + 0.045743\varepsilon^2_{2,t-1} + 0.917291h_{22,t-1}$
$h_{23} = 0.103386 + 0.032683\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.92645h_{23,t-1}$	$h_{23} = 0.009736 + 0.067585\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.872615h_{23,t-1}$
$h_{24} = 0.111866 + 0.058541\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.840972h_{24,t-1}$	$h_{24} = 0.022698 + 0.051747\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.889386h_{24,t-1}$
$h_{33} = 0.260424 + 0.038532\varepsilon^2_{3,t-1} + 0.911964h_{33,t-1}$	$h_{33} = 0.234535 + 0.099855\varepsilon^2_{3,t-1} + 0.830114h_{33,t-1}$
$h_{34} = 0.117099 + 0.069018\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 0.827827h_{34,t-1}$	$h_{34} = -0.026914 + 0.076456\varepsilon_{3,t-1}\varepsilon_{4,t-1} + 0.846069h_{34,t-1}$
$h_{44} = 0.323641 + 0.123623\varepsilon^2_{2,t-1} + 0.751452h_{22,t-1}$	$h_{44} = 0.359130 + 0.058540\varepsilon^2_{2,t-1} + 0.862330h_{22,t-1}$

In the Student-t diagonal BEKK (1,1) model for the COVID-19 period, the constant values of ε are calculated as 0.165134, 0.027722, 0.038532, and 0.123623, respectively. These values indicate the effect of volatility shocks (ARCH effect) in the S&P 500, STOXX 50, RTSI, and BIST 100 time series. These coefficients demonstrate how the volatility of each market persists based on its previous errors. For the US and Türkiye, the most significant influence over their forthcoming volatility is observed.

In the Student-t diagonal BEKK (1,1) model during the war period, the constant values of ε are determined as follows: 0.030558, 0.045743, 0.099855, and 0.058540, respectively. In contrast to the COVID-19 period, Russia has the biggest impact on its future volatility in the war period. On the other hand, Türkiye maintains the utmost impact on its future volatility in the war period, as observed in the COVID-19 period.

For the two crisis periods, Figure 2 illustrates the estimated conditional correlations among each pair of stock market indices. The onset of turmoil dates saw notable spikes in conditional correlations, potentially attributed to the necessity for swift readjustments to cope with these fluctuations, resulting in rapid but short-lived declines.

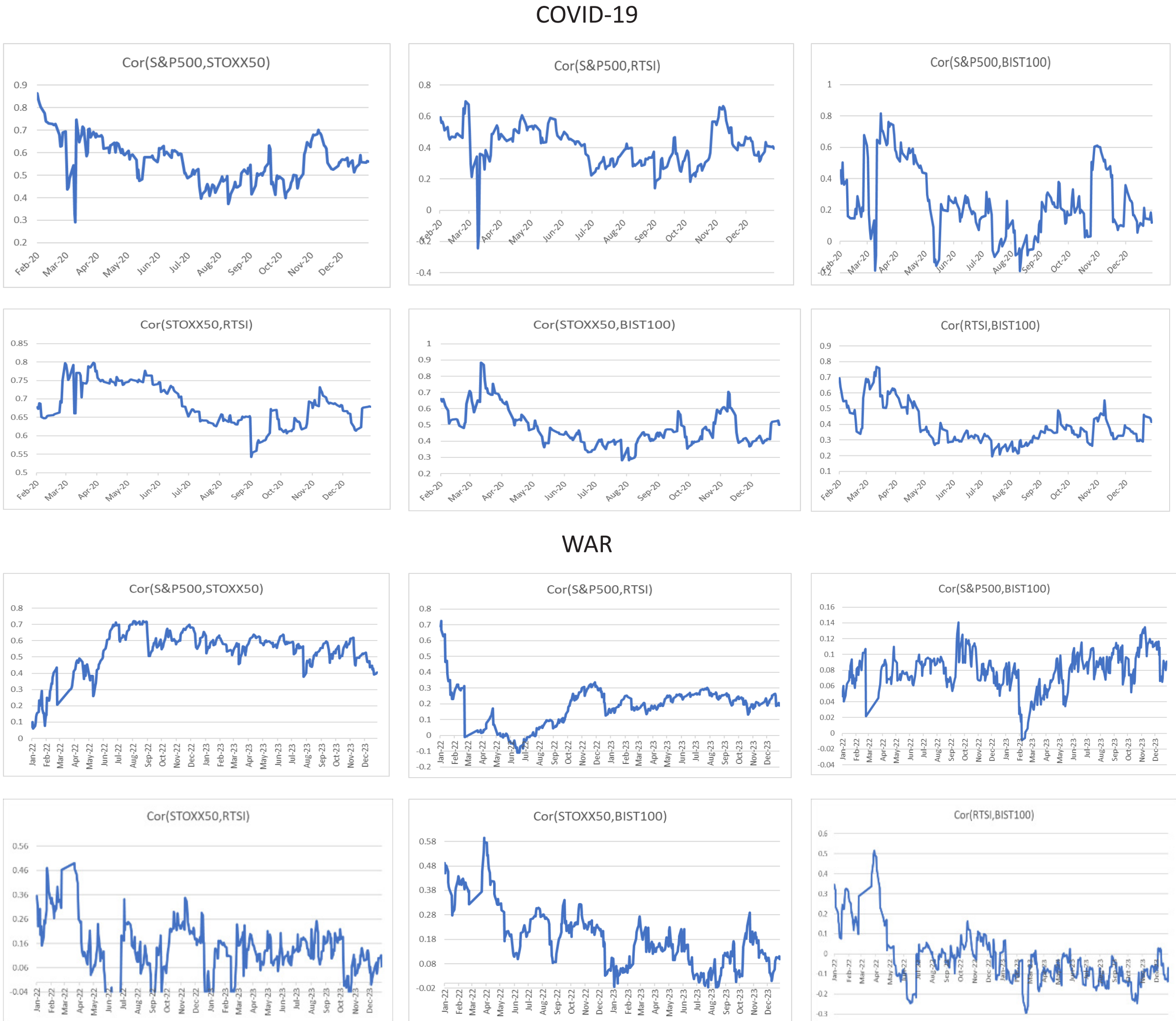


Figure 2: Pairwise conditional correlations

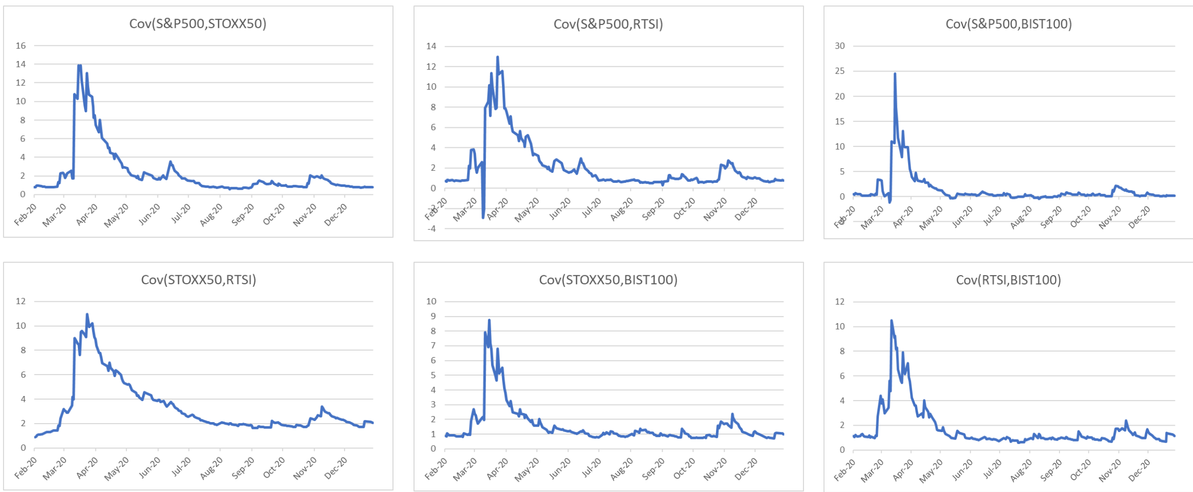
When considering the lagged own-volatility persistence (GARCH effect - h), it is observed that the coefficients for the S&P 500, STOXX 50, RTSI, and BIST 100 indices are 0.801094, 0.941157, 0.911964, and 0.751452, respectively, for the COVID-19 period. These findings indicate that European stock market relies more on volatility persistence originating from its domestic market, whereas Türkiye draws more on volatility persistence from external sources beyond its domestic market.

During the war period, the coefficients reveal intriguing dynamics: 0.959550 for the US market, 0.917291 for the Russian market, 0.830114 for the Ukrainian market, and 0.862330 for the domestic market. These coefficients shed light on the intricate relationships within and across markets during the turbulent period of the Russia-Ukraine conflict. Specifically, they suggest that while a significant portion of US volatility persistence originates from its own domestic market, Russian volatility is notably influenced by external factors. Moreover, the internal volatility spillover effects among the four exchanges exhibit considerable diversity, underscoring the nuanced risk-return profiles and varying sensitivities to external shocks inherent in each financial market. Such findings underscore the complexity of inter-market dynamics during times of geopolitical turmoil and underscore the need for a comprehensive understanding of cross-market interactions.

Furthermore, the transmission of volatility stemming from domestic factors to the exchanges is not consistently limited to specific boundaries during these crisis periods. This suggests that each emerging market exhibits a unique risk-return profile and susceptibility to external influences beyond its control.

When the conditional correlation graphs in Figure 3 are considered, it is seen that there is a very variable correlation between the markets. Therefore, the use of conditional correlation methods for the US, European, Russian, and Turkish markets shows that it can be more successful and advantageous with diversification in terms of investment.

COVID-19



WAR

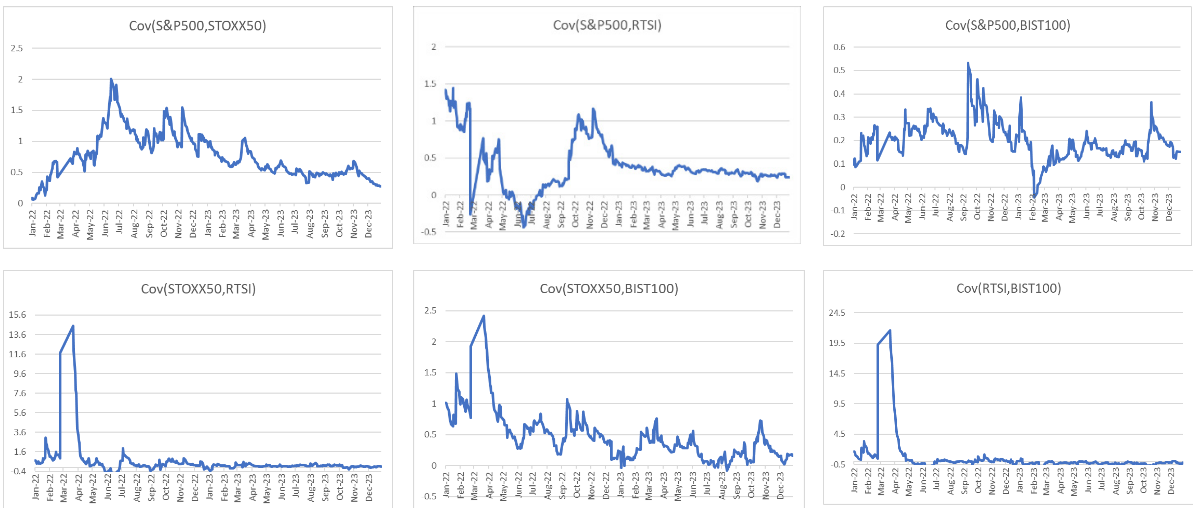


Figure 3: Pairwise conditional covariances

During the COVID-19 period, for the US, the lagged cross-volatility persistence ranges from 0.86830 (Europe) to 0.775876 (Türkiye), while in Europe, it ranges from 0.92645 (Russia) to 0.84097 (Türkiye). In Russia, cross-volatility persistence ranges from 0.92645 (Europe) to 0.827827 (Türkiye), whereas in Türkiye, it ranges from 0.840972 (Europe) to 0.775876 (US) during the COVID-19 period. Therefore, concerning cross-volatility persistence, Türkiye is found to be the market with the least influence in the study, while Europe appears to exert the most significant influence. Moreover, cross-volatility spillovers surpass own volatility spillovers for all countries except Europe; in other words, Europe is least vulnerable to external shocks.

During the war period, it is observed that the lagged cross-volatility persistence exhibits distinct patterns across different countries. Specifically, for the United States, this persistence ranges from 0.938182 when compared with Europe to 0.892489 when compared with Russia. In Europe, the cross-volatility persistence with the US ranges from 0.938182 to 0.872615 when compared with Russia. Notably, Russia’s cross-volatility persistence varies from 0.892489 in comparison with the US to 0.846069 when compared with Türkiye. Conversely, in Türkiye, this persistence ranges from 0.909642 when compared with the US to 0.846069 when compared with Russia. Consequently, it can be inferred that, in terms of cross-volatility persistence, the United States exerts the most substantial influence, whereas Türkiye demonstrates the least influence during this period of analysis.

The analysis reveals that while cross-volatility persistence varies across four stock markets, the least influential market remains consistent between the COVID-19 and war periods. However, there is a change in the most influential market. Notably, the study finds a consistent positive impact of lagged covariance on future covariance across all pairs, with coefficients ranging from 0.846069 (Russia-Türkiye) to 0.938182 (US-Europe). These results suggest that the level of persistence in cross-market volatility may not solely be determined by geographical proximity or economic connections among nations, but rather by the degree of market integration with the global economy.

6.CONCLUSION

The application of the diagonal BEKK model allowed for a comprehensive analysis of the American, European, Russian, and Turkish stock markets. This analysis aimed to investigate how the conditional expectation and covariance equations captured the volatility and cross-volatility dynamics specific to each market, particularly during recent crises. The study encompassed both emerging and developed countries, providing insights into the behavior of financial markets across diverse economic landscapes. Results show that there is an ARCH and GARCH effect between the markets. Moreover, according to the diagonal BEKK GARCH equations constructed across markets, volatility changes in one market can spread to other markets during COVID-19 and the war period. These results indicate the existence of relatively weaker ARCH effects and stronger GARCH effects. The results obtained are consistent with the literature (Bozma and Yasar, 2018; Erten et al., 2012).

During both the COVID-19 pandemic and war periods, it has been observed that own volatility spillovers are most pronounced in the US and Europe, compared to Russia and Türkiye. This can be explained by the US and European markets have very high market liquidity and trading volumes. These findings suggest a higher degree of persistence in volatility for each country, as indicated by their respective past errors. A significant level of spillover implies reduced market efficiency, consistent with previous research (Bollerslev and Hodrick, 1995). Specifically, throughout the COVID-19 period, Europe exerts the most substantial influence on the future volatility of market returns in the US, Russia, and Türkiye. Conversely, during the war period, the US emerges as the dominant influencer on the future volatility of market returns in Europe, Russia, and Türkiye.

The primary reasons why European market returns exerted the most significant influence on the future volatility of the US, Turkish, and Russian markets during the COVID-19 period can be attributed to the high level of integration of European markets within global financial systems and the substantial trade partnerships between Europe and these economies. It is likely that pandemic-related measures, central bank policy interventions directly affecting market dynamics, and trade restrictions in Europe contributed to the observed volatility transmission to other markets.

The heightened impact of US stock markets on the future volatility of other markets during the war period can be explained by several factors: the extensive economic sanctions imposed by the US on Russia, the US Federal Reserve's interest rate hikes and liquidity tightening policies—both of which prompted capital outflows from countries like Europe, Russia, and Türkiye—and European countries' decisions to reduce energy dependence on Russia, increasingly sourcing energy from the US in the process.

During both the COVID-19 pandemic and the wartime period, the US and Turkish markets exhibited high volatility, indicating significant susceptibility to external shocks. As the global reserve currency, the US dollar and related economic indicators are closely monitored by investors worldwide. In times of global crisis, investors often view the US markets as a safe haven, intensifying volatility. Additionally, the US's extensive financial and commercial ties with other economies mean that global crises directly impact the US economy and, consequently, its stock market. In Türkiye, macroeconomic vulnerabilities such as high inflation and limited foreign exchange reserves heighten sensitivity to global crises. This can lead to increased fragility in the Turkish stock market during turbulent periods, with foreign investors rapidly exiting based on shifts in risk perception. Such swift entry and exit of foreign capital can further amplify market volatility.

Furthermore, the European and Russian markets exhibited lower volatility during both crises than the US and Turkish markets. The Stoxx50 index, representing European markets, is composed of large companies across various sectors, suggesting that this sectoral diversity may have mitigated the effects of a crisis in any single industry on the overall market performance. Additionally, Western Europe, alongside the US, imposed stringent sanctions on Russia during the wartime period. These sanctions, which restricted Russian markets' access to the international financial system, are believed to have contributed to the relatively lower volatility observed in Russian markets.

In summary, this study's theoretical and practical insights suggest that shifts in market volatility persistence during the COVID-19 and war periods highlight the need for investors to adjust strategies according to the nature of each crisis. The greater volatility spillover across markets observed during the COVID-19 period indicates that hedging strategies may be more effective than global diversification strategies in managing risk. Meanwhile, the higher volatility persistence of US markets during the war period suggests that long-term positioning, alongside the use of derivatives such as options and futures, or alternative investments like gold and bonds, may support risk management and portfolio optimization for investors.

This research findings reveal that investors should diversify their portfolios by incorporating not just emerging market stocks but also those from developed markets. It is crucial to consider correlations and the spillover effects of volatility between emerging and developed stock markets. Additionally, the findings indicate that risk management strategies should be tailored specifically to each period, as the distinct characteristics of each crisis require unique approaches to manage and mitigate risk effectively.

These findings will provide valuable insights for academics constructing models to explain financial market behavior, investors examining how domestic asset values might be impacted by shifts in international financial markets, and policymakers comprehending how volatility could influence investment and consumption decisions within the domestic economy.

REFERENCES

Abounoori, E., and Tour, M. (2019). "Stock market interactions among Iran, USA, Turkey, and UAE", *Physica A: Statistical mechanics and its applications*, 524, 297-305.

Aggarwal, K., and Saradhi, V. R. (2024). "A Study on the Co-Movement and Influencing Factors of Stock Markets between India and the Other Asia–Pacific Countries", *International Journal of Emerging Markets*.

Akarsu, G. (2022). "Volatility Spillover among BIST Sector Indices, SP500 Index and USD/TRY Exchange Rate: Stochastic Volatility Modelling", *VI. Anadolu Uluslararası* İktisat *Kongresi* Özetler *Kitabı*, (s73), 13-15.

Alaoui Mdaghri, A., Raghibi, A., Thanh, C. N., and Oubdi, L. (2021). "Stock market liquidity, the great lockdown and the COVID-19 global pandemic nexus in MENA countries", *Review of Behavioral Finance*, 13(1), 51-68.

Alkan, B., and Çiçek, S. (2020). "Spillover Effect in Financial Markets in Turkey", *Central Bank Review*, 20(2), 53-64.

Aslam, F., Ferreira, P., Mughal, K. S., and Bashir, B. (2021). "Intraday Volatility Spillovers among European Financial Markets during COVID-19", *International Journal of Financial Studies*, 9(1),

Anyikwa, I. C., and Phiri, A. (2023). "Dynamics of Return and Volatility Spill-Over between Developed, Emerging and African Equity Markets during the COVID-19 Pandemic and Russia–Ukraine War", *Studies in Economics and Econometrics*, 1-25.

Ayadi, C., and Said B. H. (2023). "COVID-19 pandemic and stock market volatility spillovers". *Journal of Financial Reporting and Accounting,* 1985-2517.

Barua, S. (2020). "Understanding Coronanomics: The economic implications of the coronavirus (COVID-19) pandemic", Available at SSRN 3566477.

Bayramoğlu, M. F., and Abasız, T. (2017). "Gelişmekte olan Piyasa Endeksleri Arasında Volatilite Yayılım Etkisinin Analizi", *Muhasebe ve Finansman Dergisi*, (74), 183-200.

Belasri, Y. and Ellaia, R (2017). "Estimation of Volatility and Correlation with Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models: An Application to Moroccan Stock Markets", *International Journal of Economics and Financial Issues*, 7(2), 384-396.

Belke, A., and Dubova, I. (2018). "International spillovers in global asset markets", *Economic Systems*, 42(1), 3-17.

Bhar, R., and Nikolova, B. (2007). "Analysis of mean and volatility spillovers using BRIC countries, regional and world equity index returns", *Journal of Economic Integration*, 369-381.

Bollerslev, T. Engle, R. F. and Wooldridge, J. M. (1988), "A Capital Asset Pricing Model With Time-Varying Covariances", *Journal of Political Economy*, 96(1), 116-131.

Bollerslev, T. (1986). "Generalized autoregressive conditional heteroskedasticity", *Journal of econometrics*, 31(3), 307-327.

Bollerslev, T. (1990), "Modelling the coherence in short-run nominal exchange rates: a multivariate generalized approach", *Review of Economics and Statistics*, 72, 498-505.

Bollerslev, T. and Hodrick, R.J. (1995). "Financial market efficiency tests", *Handbook of Applied Econometrics*, Vol. 1, 415-458.

Bozma, G., İmamoğlu, İ. K., and Künü S. (2023). "Dynamic Volatility Spillover among Emerging Eagle Markets", *Ekonomik ve Sosyal Araştırmalar Dergisi*, 19(2), 316-336.

Bozma, G. and Başar, S. (2018). "Analyzing Volatility Transmissions between Stock Markets of Turkey, Romania, Poland, Hungary and Ukraine using M-GARCH Model", *Hacettepe* Üniversitesi İktisadi *ve* İdari *Bilimler Fakültesi Dergisi*, 36(4), 1-15.

Cheng, Z., Li, M., Cui, R., Wei, Y., Wang, S., and Hong, Y. (2024). "The impact of COVID-19 on global financial markets: A multiscale volatility spillover analysis", *International Review of Financial Analysis*, 95, 103454.

Darrat, A. F. and Benkato, O. M. (2003). "Interdependence and volatility spillovers under market liberalization: The case of Istanbul stock exchange", *Journal of Business Finance & Accounting*, 30(7-8), 1089-1114.

Diebold, F. X., and Yilmaz, K. (2012). "Better to give than to receive: Predictive directional measurement of volatility spillovers", *International Journal of forecasting*, 28(1), 57-66.

Engle, R. (2001), "GARCH 101: The Use Of ARCH/GARCH Models In Applied Econometrics", *Journal of Economic Perspectives*, 15(4), 157-168.

Engle, R. F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation", *Econometrica: Journal of the econometric society*, 987-1007.

Engle, R. F. and Kroner, K. F. (1995). "Multivariate Simultaneous Generalized ARCH", *Econometric Theory*, 11(1), 122-150.

Erer, E., Erer, D., and Korkmaz, Ö. (2019). "Farklı Rejimler Altında Türkiye, İngiltere, Amerika ve Euro Bölgesi Tahvil Piyasaları, Emtia Piyasası ve Döviz Piyasasından BIST100 Endeksine Volatilite Yayılımı", BDDK Bankacılık ve Finansal Piyasalar Dergisi, 13(1), 77-103.

Erten, I., Tuncel, M. B., and Okay, N. (2012). "Volatility Spillovers in Emerging Markets during the Global Financial Crisis: Diagonal BEKK Approach". https://mpra.ub.uni-muenchen.de/56190/

Eun, C. S., and Shim, S. (1989). "International transmission of stock market movements", *Journal of Financial and Quantitative Analysis*, 24(2), 241-256.

Gheorghe, C., and Panazan, O. (2023). "Effects of Information Related to the Russia-Ukraine Conflict on Stock Volatility: An EGARCH Approach", *Cogent Economics and Finance*, 11(2), 2241205.

Gong, X., Zeng, X., Xu, W., and Zhang, W. (2023). "Asymmetric risk spillovers and its determinants in global equity markets", *Physica A: Statistical Mechanics and its Applications*, 624, 128926.

Gürsoy, S., and Eroğlu, Ö. (2016). "Yükselen Ekonomilerin Pay Piyasalari Arasında Getiri ve Volatilite Yayılımı: 2006-2015 Yıllari Arasında Yapılmış Bir Analiz", *Mehmet Akif Ersoy* Üniversitesi İktisadi *ve* İdari *Bilimler Fakültesi Dergisi*, 3(1), 16-33.

Jain, P., and Sehgal, S. (2019). "An examination of return and volatility spillovers between mature equity markets", *Journal of Economics and Finance*, 43(1), 180-210.

Jude, O., Turgeman, A., Boțoc, C., and Miloș, L. R. (2023). "Volatility and Spillover Effects between Central–Eastern European Stock Markets and Energy Markets: An Emphasis on Crisis Periods", *Energies*, 16(17), 6159.

Karğin, S., Kayalidere, K., Güleç, T. C., and Erer, D. (2018). "Spillovers of Stock Return Volatility to Turkish Equity Markets from Germany, France, and America", *Dokuz Eylül* Üniversitesi *Sosyal Bilimler Enstitüsü Dergisi*, 20(2), 171-187.

Khan, M., Khan, M., Kayani, U. N., Mughal, K. S., and Mumtaz, R. (2023). "Unveiling Market Connectedness: Dynamic Returns Spillovers in Asian Emerging Stock Markets", *International Journal of Financial Studies*, 11(3), 112.

Kırkulak Uludag, B., and Khurshid, M. (2019). "Volatility spillover from the Chinese stock market to E7 and G7 stock markets", *Journal of Economic Studies*, 46(1), 90-105.

Kocaarslan, B. (2020). "ABD Finansal Piyasalarındaki Gelişmelerin ve Belirsizliklerin Borsa İstanbul Üzerindeki Asimetrik Etkileri", *Anemon Muş Alparslan* Üniversitesi *Sosyal Bilimler Dergisi*, 8, 33-42.

Korkmaz, T., and Çevik, E. İ. (2009). Zımni volatilite endeksinden gelişmekte olan piyasalara yönelik volatilite yayılma etkisi. *BDDK Bankacılık ve Finansal Piyasalar*, 3(2), 87-105.

Koutmos, G., and Booth, G. G. (1995). "Asymmetric volatility transmission in international stock markets", *Journal of international Money and Finance*, 14(6), 747-762.

Kumar, R. M., and Koushik, K. (2023). "Volatility Spillover between Russia and European Stock Markets", *Current Research in Mutual Funds and Stock Market*, 7.

Kutlu, M., and Karakaya, A. (2021). "Return and volatility spillover effects between the Turkey and the Russia stock market", *Journal of Economic and Administrative Sciences*, 37(4), 456-470.

Lee, B. S., and Rui, O. M. (2002). "The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence", *Journal of Banking & Finance*, 26(1), 51-78.

Li, J., Wang, R., Aizhan, D., and Karimzade, M. (2023). "Assessing the Impacts of COVID-19 on Stock Exchange, Gold Prices, and Financial Markets: Fresh Evidences from Econometric Analysis", *Resources Policy*, 83,

Li, L., Yin, L., and Zhou, Y. (2016). "Exogenous shocks and the spillover effects between uncertainty and oil price", *Energy Economics*, 54, 224-234.103617.

Li, W. (2021). "COVID-19 and asymmetric volatility spillovers across global stock markets", *The North American Journal of Economics and Finance*, 58, 101474.

Li, W., Chien, F., Kamran, H.W., Aldeehani, T.M., Sadiq, M., Nguyen, V.C. and Taghizadeh-Hesary, F. (2022), "The nexus between covid-19 fear and stock market volatility", *Economic ResearchEkonomska Istraživanja*, 35 (1), 1765-1785

Li, Y., and Giles, D. E. (2015). "Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets", *International Journal of Finance & Economics*, 20(2), 155-177.

Liu, C. (2016). "Spillover effects in major equity markets: A GARCH BEKK approach", *Open Access Library Journal*, 3(02), 1–21.

Liu, Q., Xu, C., and Xie, J. (2024). “Comparative Analysis of Spillover Effects in the Global Stock Market under Normal and Extreme Market Conditions”, *International Journal of Financial Studies*, 12(2), 53.

Liu, X., An, H., Li, H., Chen, Z., Feng, S., and Wen, S. (2017). “Features of spillover networks in international financial markets: evidence from the G20 countries”, *Physica A: Statistical Mechanics and its Applications*, 479, 265-278.

Markowitz, H.M. (1952). “Portfolio Selection”, *The Journal of Finance*. Blackwell Publishing, 7(1), 77-91.

Maurya, P. K., Bansal, R., and Mishra, A. K. (2024). “Dynamic connectedness among market volatilities: a perspective of COVID-19 and Russia-Ukraine conflict”, *Studies in Economics and Finance*.

Mensi, W., Hammoudeh, S., Reboredo, J. C., and Nguyen, D. K. (2014). “Do global factors impact BRICS stock markets? A quantile regression approach”, *Emerging Markets Review*, 19, 1-17.

Mensi, W., Shafiullah, M., Vo, X. V., and Kang, S. H. (2021). “Volatility spillovers between strategic commodity futures and stock markets and portfolio implications: Evidence from developed and emerging economies”, *Resources Policy*, 71, 102002.

Mezghani, T., Ben Hamadou, F., and Boujelbène Abbes, M. (2021). “The dynamic network connectedness and hedging strategies across stock markets and commodities: COVID-19 pandemic effect”, *Asia-Pacific Journal of Business Administration*, 13(4), 520-552.

Nandy, S., and Chattopadhyay, A. K. (2019). ‘Indian stock market volatility’: A study of inter-linkages and spillover effects. *Journal of Emerging Market Finance*, 18(2_suppl), S183-S212.

Özdemir, L. (2020), “Testing for Asymmetric Causality Between Developed and Emerging Markets”, Özen, E. and Grima, S. (Ed.) *Uncertainty and Challenges in Contemporary Economic Behaviour (Emerald Studies in Finance, Insurance, and Risk Management)*, Emerald Publishing Limited, Leeds, 145-158.

Özün, A., and Ertuğrul, H. (2014). “Variance-Based Spillover Analysis between Stock Markets: A Time Varying Parameter Approach”, *Acta Physica Polonica A*, 125(1), 155-157.

Pan, Q., Mei, X., and Gao, T. (2022). “Modeling dynamic conditional correlations with leverage effects and volatility spillover effects: Evidence from the Chinese and US stock markets affected by the recent trade friction”, *The North American Journal of Economics and Finance*, 59, 101591.

Panda, A. K., Nanda, S., and Paital, R. R. (2019). “An empirical analysis of stock market interdependence and volatility spillover in the stock markets of Africa and Middle East region”, African Journal of Economic and Management Studies, 10(3), 314–335.

Panda, P., Vasudevan, S., and Panda, B. (2021). “Dynamic connectedness among BRICS and major countries stock markets”, *Journal of Public Affairs*, 21(3), e2265.

Prasad, S. S., Verma, A., Bakhshi, P., and Prasad, S. (2023). “Global Stock Market Volatility and Its Spillover on the Indian Stock Market: A Study Before and During the COVID-19 Period”, *FIIB Business Review*, 23197145231189600.

Rastogi, S., and Kanoujiya, J. (2024). “Impact of cryptos on the inflation volatility in India: an application of bivariate BEKK-GARCH models”, *Journal of Economic and Administrative Sciences*, 40(2), 221-237.

Sahoo, S., and Kumar, S. (2024). “Volatility spillover among the sectors of emerging and developed markets: a hedging perspective”, *Cogent Economics & Finance*, 12(1), 2316048.

Sajeev, K. C., and Afjal, M. (2022). “Contagion effect of cryptocurrency on the securities market: A study of Bitcoin volatility using diagonal BEKK and DCC GARCH models”, *SN Business & Economics,* 2(6), 57.

Sinlapates, P., and Chancharat, S. (2024). “Persistence and volatility spillovers of Bitcoin to other leading cryptocurrencies: a BEKK-GARCH analysis”, *Foresight*, 26(1), 84-97.

Sezen, S., and Çevik, E. İ. (2024). “Hisse Senedi Piyasaları Arasında Yayılma Etkisinin Analizi”, *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty*, 11(1), 19-50.

Tien, H. T., and Hung, N. T. (2022). “Volatility Spillover Effects between Oil and GCC Stock Markets: A Wavelet-Based Asymmetric Dynamic Conditional Correlation Approach”, *International Journal of Islamic and Middle Eastern Finance and Management*, 15(6), 1127-1149.

Tsay, R. S. (2005). *Analysis of Financial Time Series*. The University of Chicago- Booth School of Business. John wiley & sons INC., Publication. 3rd edition, Chicago, IL.

Tsuji, C. (2024). "The historical transition of return transmission, volatility spillovers, and dynamic conditional correlations: A fresh perspective and new evidence from the US, UK, and Japanese stock markets", *Quantitative Finance and Economics*, 8(2), 410-436.

Vo, X. V., and Tran, T. T. A. (2020). "Modelling volatility spillovers from the US equity market to ASEAN stock markets", *Pacific-Basin Finance Journal*, 59, 101246.

Wang, Y., Bouri, E., Fareed, Z., and Dai, Y. (2022). "Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine", *Finance Research Letters*, 49, 103066.

Wu, F. L., Zhan, X. D., Zhou, J. Q., and Wang, M. H. (2023). "Stock Market Volatility and Russia–Ukraine Conflict", *Finance Research Letters*, 55: 103919.

Yadav, M. P., Sharma, S., and Bhardwaj, I. (2023). "Volatility Spillover between Chinese Stock Market and Selected Emerging Economies: A Dynamic Conditional Correlation and Portfolio Optimization Perspective", *Asia-Pacific Financial Markets*, 30(2), 427-444.

Yıldırım, D., and Çelik, A. K. (2020). "Stock Market Volatility and Structural Breaks: An Empirical Analysis of Fragile Five Countries Using GARCH and EGARCH Models", *Journal of Applied Economics and Business Research*, 10(3), 148-163.

Yılmaz, K. (2010). "Return and volatility spillovers among the East Asian equity markets", *Journal of Asian Economics*, 21(3), 304-313.

Yuan, Y., and Du, X. (2023). "Dynamic spillovers across global stock markets during the COVID-19 pandemic: Evidence from jumps and higher moments", *Physica A: Statistical Mechanics and its Applications*, 628, 129166.

Yousef, I. (2020). "Spillover of COVID-19: Impact on Stock Market Volatility", *International Journal of Psychosocial Rehabilitation*, 24(6), 18069-18081.

Yousaf, I., Mensi, W., Vo, X. V., and Kang, S. H. (2024). "Dynamic spillovers and connectedness between crude oil and green bond markets", *Resources Policy*, 89, 104594.

Zhang, D., Hu, M., and Ji, Q. (2020). "Financial markets under the global pandemic of COVID-19", *Finance research letters*, 36, 101528.

Zhang, W., and Hamori, S. (2021). "Crude oil market and stock markets during the COVID-19 pandemic: Evidence from the US, Japan, and Germany", *International Review of Financial Analysis*, 74, 101702.

Zhong, Y., and Liu, J. (2021). "Correlations and volatility spillovers between China and Southeast Asian stock markets", *The Quarterly Review of Economics and Finance*, 81, 57-69.

Zhou, Y., Wu, S., and Liu, Z. (2023). "Does the COVID-19 pandemic strengthen the volatility spillovers across global stock markets?", *International Journal of Financial Engineering*, 2350043.

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