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Effects of information related to the Russia-Ukraine conflict on stock volatility: An EGARCH approach

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Abstract: The Russia-Ukraine military conflict, commencing on February 24, 2022, notably impacted the international community. This study aims to quantify the volatility engendered by the conflict, drawing from the analysis of stock market indices across 40 countries. Time-series returns data from January 1 to December 31, 2022, were examined utilizing EGARCH econometric models. The relationship between volatility and news regarding the conflict was analyzed through a vector autoregression model, and associations between variables were examined using the Granger causality test. Findings suggest that some markets proximate to Ukraine, notably in Hungary, Polassnd Poland, Serbia, Bosnia and Herzegovina, and the Czech Republic, reacted in anticipation of the conflict, days prior to February 24. Remote markets experienced comparatively lower volatility, along with the primary stock markets. Additionally, a decline in volatility was observed as war-related information became available. Notably, the period between March 2 and March 16, 2022, recorded the highest volatility in 21 countries. Conversely, the value markets of the US, China, Japan, the UK, and Germany navigated the analyzed period with lower volatilities. These results demonstrate that conflict shocks influence stock markets globally. The implications of these findings are significant for investors, decision-makers, portfolio managers, investment funds, and central banks.

Subjects: Economics; Finance; Business

Keywords: volatility; Russia-Ukraine war; EGARCH; vector autoregression model; Granger; asymmetric effect

1. Introduction

The conflict between Russia and Ukraine began on 24 February 2022 (Neely, 2022) and has strongly impacted global markets. Major military actions; the blocking of Ukrainian export flows; sanctions imposed on Russia by international organizations, countries, and private companies; and the limitation of Russia's exports were the main determinants of imbalances on a global scale (Ihle et al., 2022). This instability is a result of the fact that both countries export large amounts of food, energy, metals, and minerals (https://data.worldbank.org).

The analysis period enabled the identification of significant moments after the beginning of the military conflict. Russia recognized the independence of the two Ukrainian states on 21 February 2022. This situation received a strong, unfavorable reaction (Ahmed et al., 2022). Early signs of the impending invasion appeared in late October 2021, when Russian troops started maneuvering unusually close to the Ukrainian border. The Russian president recognized the Lugansk and Donetsk People's Republics and directed troops into Ukrainian rebel areas on 21 February 2022. The following day, the president of the United States (US) announced that Russia had invaded Ukraine. On the same day, sanctions on Russia were imposed by the US, the United Kingdom, the European Union, Canada, Australia, Japan, and other nations. On 23 February 2022, the president of Russia officially announced "special military operations" occurring in eastern Ukraine. The Russian military invaded Ukraine on a large scale on February 24, with attacks coordinated in four directions. On the same day, the president of Ukraine deployed the armed forces and imposed a travel ban on all males between the ages of 18 and 60 (Neely, 2022).

The Russia—Ukraine conflict has detrimentally impacted stock markets through monetary, financial, and political channels. As a prominent supplier of natural gas and crude oil via pipelines crisscrossing Europe, Russia's crisis reverberated throughout its European trading partners. Russia and Ukraine are also key sources of food, raw materials, and fertilizers for European nations. The increased geopolitical danger in the Euro region negatively impacted share prices, raised investor uncertainty, and reduced corporate confidence (Caldara & Iacoviello, 2022).

Research into war-induced events and their ramifications are underrepresented within the realm of extreme negative events negative events (Kumari et al., 2023). The uncertainty and paucity of reliable information concerning the duration, scope, and impacts of the war limit research. Studies on major military conflicts were identified through relevant research portals. Bradford and Robison (1997), measured the impact of the Iraqi invasion of Kuwait on financial markets. Fernandez (2008) also investigated the Iraqi invasion and how it affected financial markets worldwide. Choudhry (2010) investigated how significant World War II events affected structural changes in the dynamics of the Dow Jones Industrial Average, using daily data from January 1939 to December 1945. Hudson and Urquhart (2015) highlighted the negative effects of the World War II on the British stock market. These findings demonstrate that significant wartime events precipitate price changes and market volatility structural disruptions.

The literature on volatility experienced substantial growth during the COVID-19 pandemic, with researchers endeavoring the determinants of financial market volatility. To assess volatility during the pandemic, researchers employed various approaches such as: breakpoint analysis (Pandey & Kumari, 2021), level of markets' information efficiency (Zhang & Mao, 2022), contagion effect (Akhtaruzzaman, Benkraiem, et al., 2022; Yousaf, 2021; Yousaf et al., 2022b), safe heaven assets (Akhtaruzzaman et al., 2021; Ali et al., 2022; Corbet et al., 2020) and others. Some research during the pandemic considered the effect of news on stock market volatility (Akhtaruzzaman, Benkraiem, et al., 2022; Yousaf et al., 2022a). Several researchers used Google Trends search data as a proxy for COVID-19 related uncertainty (Del Deb, 2023; Lo et al., 2022; Mezghani et al., 2021; Szczygielski et al., 2021). Despite these significant advances, the pathways, direction, and amplitude of volatility cannot be definitively determined.

Through a comprehensive review of the literature, we incorporated several studies that examined various facets of war-induced stock market shifts. Ha (2023) studied the volatility of several markets between January 2018 and April 2022, while Adekoya et al. (2023) focused on key oil and stock markets in their analysis. Similarly, Yousaf et al. (2022b) conducted an applicable study, evaluating abnormal returns of the G20 nations before and after 24 February 2022. Lo et al. (2022) provided the most comprehensive study, encompassing 73 countries, and examined asset prices and volatility triggered by the Russian-Ukrainian war. Fang and Shao (2022) and Khalfaoui et al. (2023) conducted studies on cryptocurrency dynamics following the inception of military operations in Ukraine.

Boubaker et al. (2022) showed that invasion generated negative abnormal returns for MSCI indices. Notably, existing studies on volatility have primarily focused on developed states or have encompassed brief timeframes—ranging from several days to weeks—following the conflict's onset. In contrast, our analysis extends over a longer period, facilitating a comprehensive evaluation of volatility dynamics. Furthermore, our analysis incorporates 40 countries across various continents, enabling us to capture the transference of volatility over different geographical distances.

Our key findings reveal that some markets responded prior to February 24, with developed markets demonstrating greater stability, slower and less pronounced reactions. Volatility was found to be contingent on the geographic proximity to the conflict zone, with markets at greater distances experiencing reduced volatility, and those closer showing increased volatility. Maximum volatility was recorded between March 2 and 16 March 2022. We also noted a decline in volatility as war-related information surfaced. These outcomes underscore the influence of conflict shocks on global stock markets and identify the least and most affected markets in terms of volatility. We also highlight a clustering tendency among the European states included in our study.

This study contributes to the existing literature in several ways. First, it analyzes the effects of the most significant post-World War II military events on stock markets. Second, it enables the establishment of volatility in countries neighboring Ukraine and Europe. Third, this analysis allows for determining the day each analyzed index reaches its maximum volatility. We complete the information related to the dynamics of stock markets by studying volatility. The large number of states considered in the analysis and the geographical arrangement of the states allow us to obtain a global picture of the impact of the ongoing military conflict.

The remainder of this study is organized as follows: The second section summarizes the literature on volatility caused by military events. The third section discusses the research approach, while the fourth section presents and elucidates the findings. The final section presents the results' limitations and future research directions. Our motivation for this study stems from the necessity to assess the impact of the war between Russia and Ukraine on stock markets to provide users with relevant information.

Literature

The literature on volatility has grown, especially since the COVID-19 pandemic. Consequently, investors, companies, financial organizations, and authorities have developed novel tactics to manage the vulnerabilities, capabilities, and risks generated by capital market volatility. Researchers have created varied models to study market resilience regarding various shocks and managing related risks, such as military and political events (Ahmed et al., 2022). Recent studies demonstrating the direction, amplitude, and frequency of volatility generated by a large-scale military conflict are insufficient—possibly because a military conflict in Europe was unlikely until February 2022.

According to efficient market theory, the price of an asset is typically affected by all information regarding future supply or demand (Fama, 1970). The dispute between Russia and Ukraine had a definite starting point in 2014, intensifying and leading to a full-scale war. Financial markets should capitalize on the effects of future events, such as war. Considering that there were several months of warnings before the invasion of Ukraine, some researchers utilized this premise to drive their research (Ahmed et al., 2022).

Neely (2022) aimed to determine how financial markets responded in the first week of the Russia—Ukraine war. The authors noted that trade and economic restrictions imposed by both sides or neutral parties anticipated real physical disturbances and impacted financial markets. Additionally, the reactions of global academic stakeholders differed (Nazarovets & Teixeira da Silva, 2022). Russian recognition of the two Ukrainian states as autonomous territories on 21 February 2022, caused substantial negative anomalous returns among European stocks (Ahmed et al., 2022). The authors recommended a thorough examination of how the global stock market crisis affected European stocks—a component that has been considered and developed in the current work. Abbassi et al. (2023) examined the impact of the Russia-Ukraine conflict on the firms that make up the main stock indices in the G7 countries. Similarly, Pandey and Kumar (2023) assessed the consequences of the war's impact on the global tourism sector. Additionally, Singh et al. (2022), using the Diebold and Yilmaz model, demonstrated that the conflict led to a change in investor preferences towards energy, defence, and the aerospace sector.

Several researchers selected geopolitical risk events (GPR) as the direction of analysis to determine the effect of the Russia—Ukraine conflict on financial markets. Political risk and the level of uncertainty in financial markets are believed to be related. Existing models, both older and recent, allow for such approaches. One example is the Economic Policy Uncertainty (EPU) Index, created by Baker et al. (2016). Additionally, Mansour-Ichrakieh and Zeaiter (2019) constructed a financial stress index to demonstrate the influence of GPR in Saudi Arabia and Russia on financial stress in Turkey. Salisu et al. (2022) revealed a correlation between the GPR and the BRICS exchange rate volatility using the GARCH-MIDAS-X model. Su et al. (2019) used wavelets to demonstrate the relationships among geopolitical risk, oil prices, and liquidity in Saudi Arabia. J. Huang et al. (2021), using the DCC-MV-GARCH model, investigated the nonlinear relationship between the oil market and GPR. X. Chen (2022) examined the impact of GPR, the CBOE Volatility Index (VIX), and EPU on Brent oil prices and stock indices in G7 nations, using data from December 1997 to April 2021. The author concluded that the EPU, VIX, and GPR have varying degrees of influence—depending on the investment horizon—with VIX being the most influential uncertainty index, followed by the EPU and GPR. Using an ARDL model, Ugurlu-Yildirim and Ordu-Akkaya (2022) measured the influence of GPR on the economies of 15 emerging markets, over a relevant period, from 1985 to 2021. Long and Guo (2022) conducted an analysis on stock volatility's effects on five infectious diseases and the GPR on five commodity categories (textiles, industry, metals, livestock, and food) over the period 1998 to 2021. The authors noted that the use of GPR, regardless of the chosen index or model, is subjective owing to the distinct nature of disruptive events.

A large number of countries imposed sanctions and limitations on Russia as a result of the crisis. The US originally announced sanctions on February 22 to restrict Russia's access to financial resources. The European Council unveiled a set of sanctions on February 23. On February 24, European leaders decided to censure Russia in the banking, energy, and transportation sectors. Moreover, they decided to impose limits on some products, implement export controls, and tighten visa requirements (Ihle et al., 2022). In contrast to prior wars, the Russia—Ukraine conflict has hampered the world's supply systems. This crisis has decreased the supply of these items because combatant governments are important producers of food, metals, oil, and gas. Furthermore, the global supply chain has been interrupted, increasing costs because of the embargo on Russian exports and Russia's unwillingness to permit international goods to pass through its skies and waterways.

Ha (2023) studied the volatility of several markets using the TPV—VAR model. The analysis was conducted from January 2018 to April 2022. The authors found that war shocks influenced dynamic connectivity at a global level. The findings indicate that the system's propagation shocks appear to be transmitted predominantly through the oil and gold markets. Adekoya et al. (2023) examined the relationship between oil prices and important share prices before and during the Russia—Ukraine war. The authors claim that the effects of conflict differ between the oil and stock markets. A different orientation has been reported by Umar et al. (2022). The authors examined how the Russia—Ukraine conflict affected markets for metals, conventional energy, and alternative energy sources. Their findings revealed a considerable increase in abnormal returns in Europe's renewable energy sector.

Lo et al. (2022) used a group of 73 countries to examine the Russia—Ukraine conflict's influence. War shocks significantly impacted financial markets; however, asset values fared better than volatility. Yousaf, et al. (2022a) evaluated the Russia—Ukraine crisis' impact on the G20 nations and other stock markets. An analysis of abnormal returns before and after 24 February 2022, revealed that most stock markets, particularly that of Russia, were significantly affected by this military action. According to a country-level analysis, the stock markets in Russia, Hungary, Slovakia, and Poland were the first to decline in the days before the military action in Ukraine, whereas those in Australia, Germany, France, Italy, Spain, Romania, Turkey, Japan, Korea, India, and South Africa supported losses in the days after the invasion (Yousaf et al., 2022a). Bougias et al. (2022) tracked the development of the asset worth of European companies during the Russia—Ukraine war. They discovered that conflict increased asset volatility and reduced corporate security costs. Reviewing the literature shows that no previous study has evaluated the global consequences of aggression on market volatility. We test global volatility's magnitude and propagation direction to fill this gap.

The expansion of online social networks has allowed interested individuals to access large volumes of publicly available information (Engelberg & Parsons, 2011). The literature indicates that news affects how quickly stock market volatility spreads (Baek & Lee, 2021; Jiang et al., 2012; Lai et al., 2022). According to previous research, social networks have a greater impact on correlation than news, which has more pronounced implications for the persistence of volatility (Alomari et al., 2021). We considered the results of these studies when selecting an econometric model. As military events continue, determining their economic and financial consequences becomes impossible. The duration of the conflict and its political, economic, and financial implications remain uncertain. The number of victims (injured and dead) among Ukrainian civilians continues to increase (UNHCR Global Appeal 2022, 2022).

Recently, several researchers have focused on the COVID-19 pandemic. Across all continents, stock market activity decreased because of the virus's extraordinary global spread. The dynamics of stock markets over an extremely short period manifest high volatility, an aspect that indicates their degree of vulnerability to major negative events (Chahuan-Jiménez et al., 2021; De Souza & Silva, 2020; Youssef et al., 2021; Yu et al., 2021). Our review of the studies conducted during the COVID-19 pandemic reveals that volatility was driven by news about the number of deaths and illnesses (Chahuan-Jiménez et al., 2021; De Souza & Silva, 2020; Yu et al., 2021). Following these studies, we sought an extension adapted to military conflicts. We attempted to identify the number of people dead and wounded owing to the Russia—Ukraine conflict. To this end, we consulted the official websites of UNICEF (https://www.unicef.org), United Nations (https://www.un.org), Office of the High Commissioner of the United Nations for Human Rights (https://www.ohchr.org), United Nations High Commissioner of Refugees Global Appeal, (2022) (2022) (https://www.unhcr.org), European Union (https://european-union.europa.eu), Organization for Economic Cooperation and Development (https://www.oecd.org), International Monetary Fund (2022) (https://www.imf.org), World Bank (2022) (https://www.worldbank.org), North Atlantic Treaty Organization (https://www.nato.int), and Eurostat (https://ec.europa.eu/eurostat), as well as other private sites (https://www.statista.com). We identified partial data on some sites or databases, but eventually deemed it insufficient for accurate analysis.

The Google Search Volume Index was used without this information (https://trends.google.com/trends/). Different researchers have used similar solutions in recent years to explore various financial aspects, including herd behavior in international equity markets (Wanidwaranan & Padungsaksawasdi, 2022), returns and trading volumes of stocks (Lai et al., 2022), the index for EPU (Kupfer & Zorn, 2020), retail investor attention and herding behavior (Hsieh et al., 2020), stock prices and trading volume (Wu et al., 2022), fund movements, future results, and longevity of newly-released funds (H.-Y. Chen et al., 2021), links between market characteristics and investor attentiveness (Tantaopas et al., 2016), predictive capabilities of internet search data (Y. M. Huang et al., 2020), investor interest in financial markets and web search activity (H.-Y. Chen & Lo, 2019), investor attention affecting stock returns (Akarsu & Süer, 2022; Swamy et al., 2019), as well as returns, their volatility and traded volumes (Moussa et al., 2017; Perlin et al., 2017).

2. Data

To identify the impact of the Russia-Ukraine conflict on a global scale, we selected 40 countries located on different continents to ensure a diverse and comprehensive perspective. The criterion for market selection was their representativeness, with a higher proportion of European markets chosen owing to the greater impact of the war on them (Deng et al., 2022). The most representative stock market index for each country was chosen, based on capitalization and volume, with the selected indices being comparable owing to their identical starting points on a standardized scale. A comprehensive time series was compiled for each chosen stock index, comprising daily data from 1 January 2022, to 30 December 2022, sourced from the Bloomberg platform (https://www.bloomberg.com/europe). Table 1 lists the countries considered and the stock indices analyzed. Statistical data were processed using the EViews 13 software (Quantitative Micro Software, USA).

The following formula is used to determine the weekly index return ($R_{i,t}$) and weekly volatility ($\sigma_{i,t}$), using daily closing index prices:

$$R_{i,t} = ln\left(\frac{Index_{Friday,t}}{Index_{Mondey,t}}\right), \tag{1}$$

$$\sigma_{i,t} = R_{i,t}^2 \tag{2}$$

where $Index_{Monday,t}$ and $Index_{Friday,t}$ are the closing stock market index prices on Monday and Friday, respectively, in week t.

Research on uncertain financial phenomena based on newspaper information has increased in recent years, as Nonejad (2022) demonstrated. In 2006, Google Trends was designed to provide the Google Search Volume Index (GSVI). We selected Google because it has a dominant position worldwide compared to other similar service providers. According to the www.netmarketshare.com portal, Google holds the largest market share worldwide as a search engine. This algorithm reports the weekly search intensity for a particular search keyword. The GSVI was determined using the following equation (http://www.atlantis-press.com):

$$GSVI = \frac{number\ of\ queries\ for\ each\ keyword}{total\ Google\ search\ queries} \tag{3}$$

This index includes statistical information on keywords. Consequently, the search popularity of any keyword can be observed for any country over a certain period. The data collected from each user leaves a trail on Google Trends (https://trends.google.co.uk). Data were collected weekly, starting on Sundays. Therefore, we had to establish the weekly return and volatility of the indices using Relationship 1, though daily data were collected.

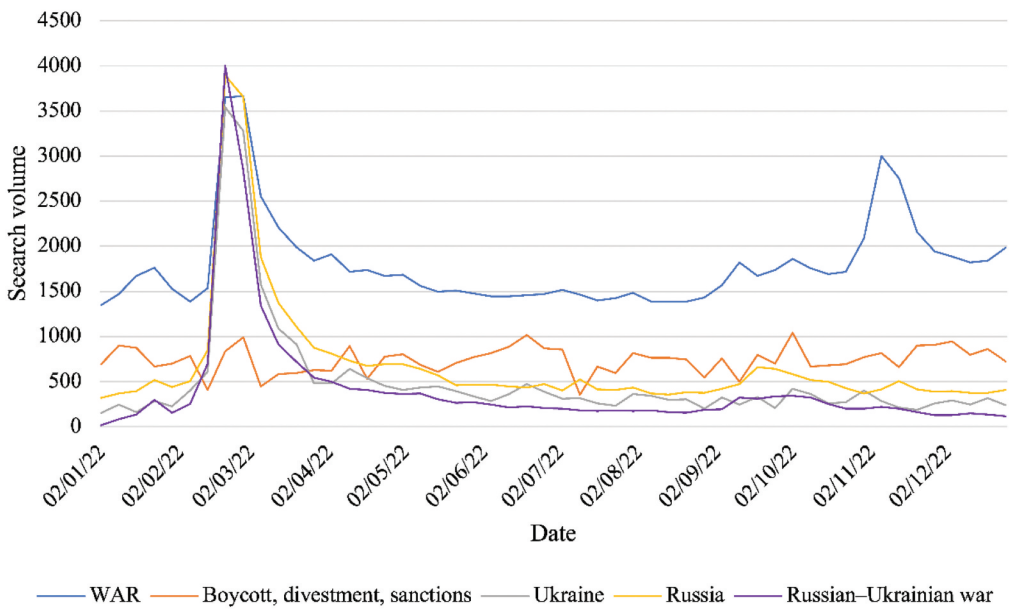
We employed search phrases in English because of several considerations. First, English is widely used by local and foreign investors. Google search algorithms prioritize English keywords over other languages, and most trading platforms use English (Anastasiou et al., 2022; Wanidwaranan & Padungsaksawasdi, 2022). The selection of appropriate search keywords is a subjective process. However, in this study, we carefully selected search keywords to ensure their relevance to the Russia-Ukraine conflict and their ability to provide valuable insights into the impact of the conflict on global markets. Among these, we retained the terms with the highest average search frequency on Google during the analyzed period, specifically, “war,” “boycott,” “disinvestment,” “sanctions,” “Ukraine,” “Russia,” and “The Russian—Ukrainian War.”

Table 1. Stock market indices

Index	State
AEX	Netherland
ASX	Australia
ATHEX	Greece
ATX	Austria
BEL20	Belgium
BELEX 15	Serbia
BET	Romania
BIRS	Bosnia and Herzegovina
BOVESPA	Brazil
BUX	Hungary
CAC40	France
CROBEX	Croatia
DAX40	Germany
FTSE MIB	Italy
FTSE 250	United Kingdom
HEX	Finland
IBEX	Spain
ICEX	Iceland
ISEQ	Ireland
JTOPI	South Africa
NIKKEI	Japan
OMX Copenhagen 20	Denmark
OMX Riga	Latvia
OMX Stockholm	Sweden
OMX Tallinn	Estonia
OMX Vilnius	Lithuania
OSEAX	Norway
PSI20	Portugal
PX	Czech Republic
RTS	Russian Federation
SAX	Slovakia
SBITOP	Slovenia
SHC	China
SMI	Switzerland
SOFIX	Bulgaria
SP500	USA
STI	Singapore
TADAWUL 30	Saudi Arabia
WIG20	Poland
XU100	Turkey

The first search keyword was "war." These terms were selected from a list of terms that Google Trends suggests are similar and have the highest number of searches. We determined the amount of news for each country and constructed a time series of equal length. Figure 1 1 depicts the news items related to each keyword.

Figure 1. Dynamics of keywords during the analyzed period.



3. Methodology

We began our analysis by checking the stationarity of the time series created. To this end, we used the Augmented Dickey—Fuller unit root test (ADF), commonly employed in volatility research (Jiang et al., 2012; Youssef et al., 2021). The equation is as follows:

$$R_t = \alpha + \beta t + \gamma R_{t-1} + \ldots + \delta_{p-1} \Delta R_{p+1} + \varepsilon_t \tag{4}$$

In this equation, α is a constant; β, the temporal trend coefficient; and *p*, the autoregressive process' lag order. There is a unit root in the studied variable when the probability of the ADF test has a *p*-value >5%, while there is no unit root when the *p*-value is 5%. The ADF test findings indicate that the variables at the first-difference levels does not have a unit root.

The Granger test establishes causality between volatility and news (Hsieh et al., 2020; Poon & Granger, 2003; Tantaopas et al., 2016). We conducted pairwise Granger causality tests for each index return. As Tantaopas et al. (2016) suggested, bidirectional causality is possible for test pairs across countries (Corbet et al., 2020; Fariska et al., 2021; Kumeka et al., 2022; Moslehpour et al., 2022).

Research aimed at determining the cause of this volatility is ongoing. A vector autoregression (VAR) model was applied to each country to underscore war news as the primary cause of volatility. Developed by Sims (1980), this model allows the use of multivariate time series. In our case, VAR is a two-variable model, wherein each variable appears as a linear expression of its previous values in a two-equation model. The historical values of each variable were considered, along with a serially uncorrelated error term.

$$R_t = \delta_1 + \sum_{j=1}^{k} \beta_j \cdot R_{t-j} + \sum_{j=1}^{k} \gamma_j \cdot GSVI_{t-j} + \varepsilon_{1t} \tag{5}$$

$$GSVI_t = \delta_2 + \sum_{j=1}^{k} \psi_j \cdot GSVI_{t-j} + \sum_{j=1}^{k} \varphi_j \cdot R_{t-j} + \varepsilon_{2t}$$

In these equations, variables δ_1 and δ_2 are free terms; β, ψ, ϕ, and γ are the coefficients; and ε_{1t} and ε_{2t} are white noise error terms (Kubiczek & Tuszkiewicz, 2022; Kumeka et al., 2022; Moslehpour et al., 2022; Zhang & Mao, 2022).

The bivariate VAR Equation 5 contains the null hypothesis (H_0) (R_t is not a cause of GSVI) and the alternative hypothesis (H_1) (R_t causes GSVI).

The econometric model was selected and applied as follows: The ARCH model, first presented by Engle (1982) and Bollerslev (1986), and the GARCH model (Bollerslev, 1986) are frequently applied to time-series research (Sims, 1980). These models simultaneously test and evaluate returns and volatility, which are meaningful because of the distinction between conditional and unconditional variances. Conditional variances depend on historical events, while unconditional variances are time-independent.

$$Y_t = \mu_t + \sigma_t \cdot z_t, z_t \sim N(0,1), \tag{6}$$

$$\varepsilon_t = \sigma_t \cdot z_t, \varepsilon_t \sim N\left(0, \sigma_t^2\right), \tag{7}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \cdot \sigma_{t-j}^2, \tag{8}$$

In these equations, σ_t^2 represents volatility comprising ARCH (q) and GARCH (p); α_0 is a constant; the parameters $\alpha_i>0$ represent the persistence of volatility; the parameters $\beta_i>0$ represent the reaction speed of volatility to market shocks; and ε_t represents the residual terms. The following condition must be satisfied to obtain a stationary covariant process (Engle, 1982):

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1. \tag{9}$$

The coefficients have negative values in the exponential GARCH model (EGARCH). Moreover, negative shocks have a greater influence on volatility than positive shocks of the same size. Consequently, the model reflects both the leverage and asymmetric effects of volatility.

$$log\left(\sigma_t^2\right) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \cdot \frac{|\varepsilon_{t-i}| + \gamma_i \cdot \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j h_{t-j}. \tag{10}$$

> In this equation, when ε_{t-i} is positive, the total effect of ε_{t-i} is $(1+\gamma_i)$; and when ε_{t-i} is negative, the total effect of ε_{t-i} is $(1-\gamma_i)|\varepsilon_{t-i}|$. Obtaining a negative value for ε_{t-i} significantly impacts volatility, whereby the value for γ_i would be negative.
>
> (Alomari et al., 2021)

4. Empirical results

4.1. Descriptive statistics

We examined the Russia—Ukraine crisis' impact on global financial markets. Appendix 1 provides statistics for the series of logarithmic returns for the entire period. Information provided by the average, median, minimum, and maximum values indicates the value range of the indices during the study period. The skewness indicator is demonstrated as having values different from zero for all series considered asymmetric. A value of less than zero indicates that the conflict has negatively impacted the observed stock market indicators. The mean skewness is located to the left of the distribution peak. Therefore, the mean value is lower than the median value and shifts to the left. Positive skewness is found in the BIRS, FTSE 250, ICEX, NIKKEI, SP 500, and XU100 stock indices, which are skewed to the right. Generally, the right tail was longer than the left tail, and most values were concentrated around the left tail.

The kurtosis indicator presents the amplitudes of extreme values. Twenty-nine indices recorded a value greater than three, while the rest had values between two and three. This finding demonstrates that the index performance is leptokurtic, and that the data series has thicker tails than a normal distribution. The analyzed series has excess kurtosis, which indicates a high probability of recording extreme values. The highest values were recorded for RTS (+13.49), BIRS (+10.08), and OMX Riga (+8.59). During the same period, the lowest values recorded were BOVESPA (+2.21), OSEAX (+2.22), and PX (+2.28). There is a zonal grouping of expectations regarding extreme values owing to the interconnection of stock markets. The skewness of most indices is negative and close to zero, as presented in Appendix 1.

The Jarque-Bera test indicates how the variables are dispersed. At the 1% critical threshold, time-series normality was ruled out as a null hypothesis, and the test's associated probability was zero. The values listed in Table 2 were established using the following relationships:

$$JB = n \cdot \left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{11}$$

In this equation, the sample size is n, sample skewness is S, and kurtosis is K (Jarque, 2011).

Figure 2. NIL.

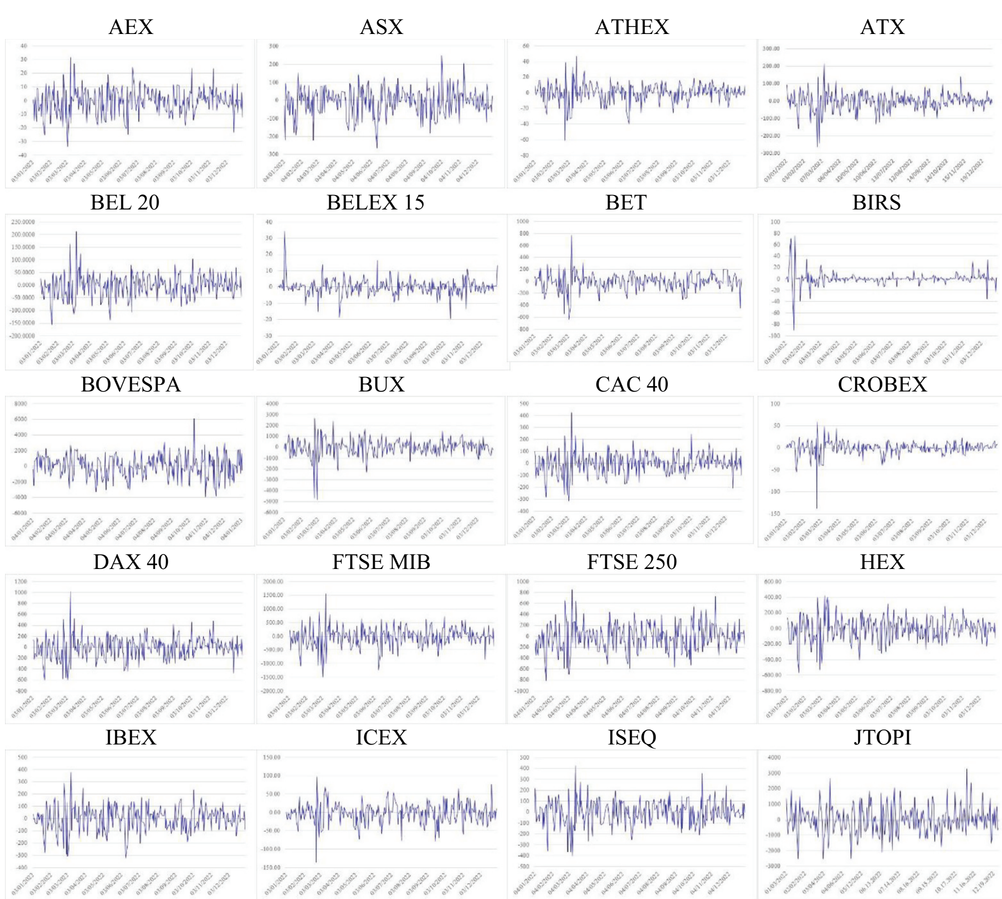
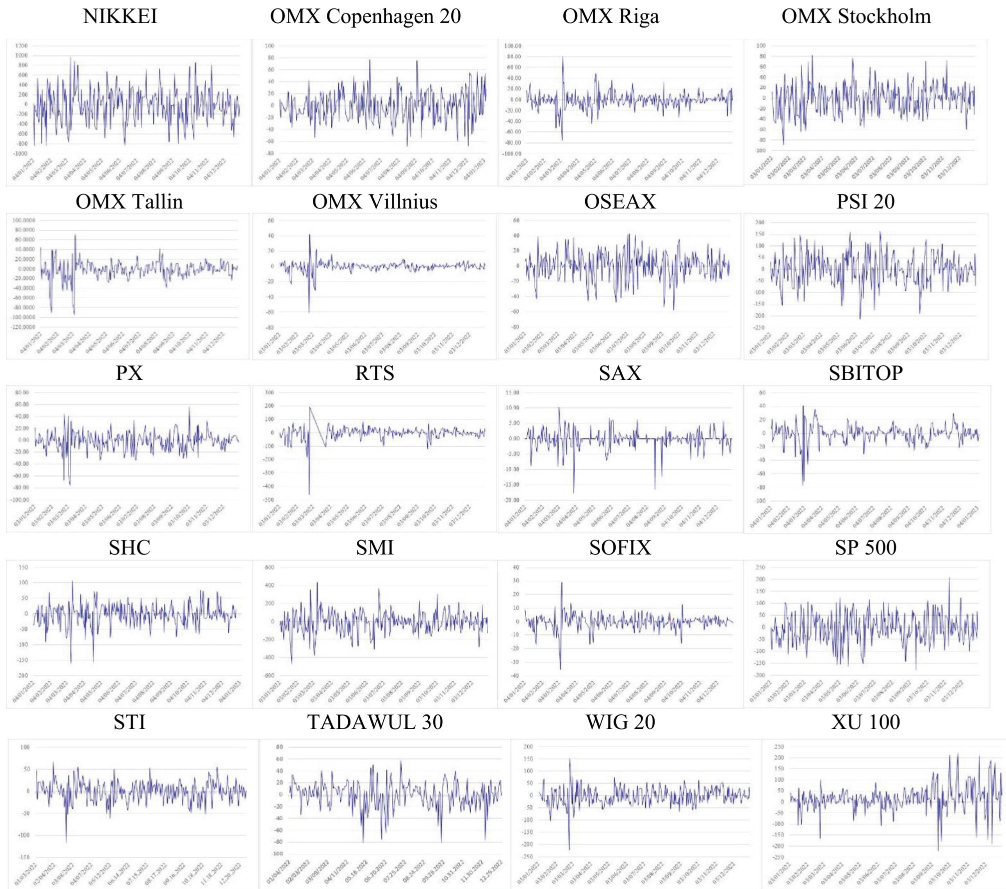


Figure 2. Daily index returns during the analyzed period.



As presented in Appendix 1, the probability is zero for 19 of the indices analyzed, wherein the numerical values obtained are extremely dissimilar to those from the normal distribution. For indices that recorded values higher than 0.01 (AEX, BELEX 15, BOVESPA, FTSE 250, ICEX, JTOPI, MSCI, NIKKEI, OMX Copenhagen, OMX Stockholm, OMX Tallinn, OSEAX, PSI 20, PX, SBITOP, SHC, SMI, SP 500, STI, WIG20, and XU 100), the risk levels were lower, as the stock markets were more stable.

4.2. ADF results

The stock indices' stationarity was investigated using the ADF test. According to the findings, the null hypothesis of a unit root was rejected as the test value was less than the crucial value for any relevance level. At the 1%, 5%, and 10% levels, the weekly logarithmic returns were significant and comparable to those obtained by Youssef et al. (2021) and Ugurlu-Yildirim and Ordu-Akkaya (2022). The statistical findings of this study indicate that the characteristic polynomial roots have a modulus smaller than one, resulting in a stable equation (see Appendix 2). As a result, the series is stationary and does not follow stochastic processes. Figure 2 shows the daily returns for all series and demonstrates the stationarity of the series.

4.3. Pairwise Granger causality

The causal connections among the variables were investigated using the Granger causality test. As presented in Appendix 3, there is unidirectional causality from news to the indices of the 21 countries analyzed. We identified six stock indices at a significance level of 5% (AEX, ATX, CROBEX, NIKKEI, PSI 20, and SMI) and 15 sat a significance level of 1% (BEL 20, BET, BUX, CAC 40, DAX 40, FTSE MIB, FTSE 250, HEX, IBEX, ISEQ, OMX Riga, OMX Stockholm, OMX Vilnius, RTS, and SOFIX). Although not long-lasting, this revealed a causal association between the GSVI and stock index volatility. No unidirectional or bidirectional causal relationship exists between the indices

Table 2. EGARCH results

Index	Coefficient	Standard error	z-Statistic	Probability
AEX	2.35E−06	6.88E−07	3.4232	.0006
ASX	1.28E−05	4.26E−06	2.996803	.0027
ATHEX	−2.40E−05	1.12E−05	−2.1366	.0326
ATX	2.58E−05	2.26E−05	1.1406	.2540
BEL 20	−1.57E−05	6.10E−06	−2.5760	.0100
BELEX 15	−1.34E−05	3.03E−06	−4.4226	.0000
BET	−3.29E−05	9.49E−06	−3.4644	.0005
BIRS	−2.40E−05	4.18E−06	−5.7529	.0000
BOVESPA	8.76E−07	1.74E−05	0.0503	.9599
BUX	−3.64E−05	1.68E−05	−2.1730	.0298
CAC 40	−4.50E−05	8.14E−06	−5.5314	.0000
CROBEX	−2.69E−05	2.81E−06	−9.5911	.0000
DAX 40	−3.94E−05	1.10E−05	−3.5823	.0003
FTSE MIB	−3.67E−05	6.97E−06	−5.2621	.0000
FTSE 250	−2.07E−05	1.03E−05	−1.9997	.0455
HEX	−4.64E−05	1.07E−05	−4.3347	.0000
IBEX	−2.64E−05	1.06E−05	−2.4891	.0128
ICEX	0.000003	2.61E−06	1.2611	.2073
ISEQ	−3.81E−05	8.14E−06	−4.6885	.0000
JTOPI	−3.89E−06	1.53E−05	−0.2543	.7992
NIKKEI	−6.60E−06	8.18E−06	−0.8070	.4196
OMX COPENHAGEN	2.07E−05	1.48E−05	1.4020	.1609
OMX RIGA	−3.00E−05	2.52E−06	−11.9226	.0000
OMX STOCKHOLM	−2.08E−05	1.05E−05	−1.9773	.0480
OMX TALLINN	−1.44E−05	7.95E−06	−1.8088	.0705
OMX VILNIUS	3.58E−06	2.39E−06	1.4984	.1340
OSEAX	−8.67E−06	7.98E−06	−1.0862	.2774
PSI 20	7.23E−06	1.04E−05	0.6963	.4862
PX	−1.77E−05	1.39E−05	−1.2725	.2032
RTS	6.69E−05	7.33E−05	0.9120	.3618
SAX	−2.67E−06	5.10E−06	−0.5239	.6003
SBITOP	−4.22E−05	7.49E−06	−5.6423	.0000
SHC	−8.50E−06	1.82E−06	−4.6680	.0000
SMI	1.35E−05	3.71E−06	3.6469	.0003
SOFIX	−1.28E−05	7.85E−06	−1.6347	.1021
SP 500	−8.81E−07	1.74E−05	−0.0506	.9596
STI	−1.39E−05	5.15E−06	−2.6974	.0070
TADAWUL 30	2.05E−08	7.01E−06	0.0029	.9977
WIG20	−4.61E−05	1.50E−05	−3.0757	.0021
XU 100	−5.04E−05	2.82E−05	−1.7882	.0737

and news, confirming the results of Kropiński and Anholcer (2022). For return volatility and GSVI, the remaining indices (AOR, ATHEX, BELEX 15, BIRS, BOVESPA, ICEX, JTOPI, MSCI, OMXC 20, OMX Tallinn, OSEAX, PX, SAX, SBITOP, SHC, SP500, STI, WIG20, and XU100) had two-way interactions, wherein the intensity of war information influences return volatility and vice versa. Further, notably, the search volume in the indices ATHEX, ICEX, MSCI, OMXC 20, SAX, SP 500, and WIG20 was determined by Granger return fluctuations.

4.4. VAR lag order check and cointegration test

Johansen's test was utilized to determine whether the time series were cointegrated (MacKinnon et al., 1999). The Johansen cointegration test is as follows:

$$Trace = -T \cdot \sum_{i=u+1}^{p} log(1 - \lambda_i)$$
$$\lambda_{Max}(r, r+1) = -T \cdot log(1 - \hat{\lambda}_{r+1}) \quad (12)$$

In this equation, p and u are components of the values INDEX and GSVI, and λ_i are the ascending Eigenvalues that provide the results (MacKinnon et al., 1999). The test was performed repeatedly for $u = p$-1, … ,0 or $u = 0$, … ,p-1 values, up to the point where the null hypothesis was rejected

$H_0 : r = r^* < k$, or until the conclusion of the series, if it is not $H_1 : r = k$ (MacKinnon et al., 1999).

The null hypothesis is accepted, and cointegration is absent when the critical values at 1%, 5%, or 10% are greater than the trace and Max-Eigen statistics (MacKinnon et al., 1999). Cointegration occurs when the null hypothesis is rejected. When a critical value at 1%, 5%, or 10% is higher than the trace and Max-Eigen statistics value, the null hypothesis is accepted, and vice versa. If the null hypothesis is not accepted, cointegration exists for the equation.

We ran a cointegration test to determine whether a long-term correlation exists between the indices and GSVI. The Akaike Information Criterion (AIC), Hannan-Quinn criterion (HQ), and Schwarz Information Criterion (SC) with the lowest values were used to determine the ideal number of lags (Ahmed et al., 2022; Mansour-Ichrakieh & Zeaiter, 2019). Based on the significance data at the 5% level and the final prediction criterion value, the number of lags (FPE) was selected (Appendix 4). The results of the analysis indicate a correlation between the indices and GSVI during the period under study (H.-Y. Chen & Lo, 2019; Kropiński & Anholcer, 2022; Lai et al., 2022; Lo et al., 2022). Appendix 5 presents the cointegration tests' findings, demonstrating that the maximum Eigenvalue and trace statistics were higher than the critical value, at a significance level of 5%. The cointegration of the indices and GSVI at a significance level of 5% leads us to conclude that the variables are in long-term equilibrium. Contrary to the null hypothesis—that cointegration cannot be denied—this finding demonstrates that the alternative is acceptable.

Subsequently, we analyzed the amplitude, direction, and duration of the links using the VAR method to determine the yield of each index (data can be provided upon request). Our results revealed a faster response in the countries surrounding Ukraine, while a significantly slower reaction was observed in developed nations. Moreover, we found a differential response according to geographical position (results available on request).

4.5. EGARCH results

Preliminary tests were performed to detect the effects of ARCH on the EGARCH model's application. To study heteroscedasticity, partial autocorrelation (PAC), autocorrelation (AC), and Q-tests were used (Youssef et al., 2021). As the p-value is typically less than 5%, the Q-test findings typically support the existence of a serial correlation. For ATX, BOVESPA, ICEX, NIKKEI, OMX COPENHAGEN, OMX TALLINN, OMX VILNIUS, OSEAX, PSI 20, PX, RTS, SAX, SOFIX, and SP500, the probabilities were greater than 5%. However, the correlation cannot be disproved up to lag 12; thus, the data series can be used in the EGARCH model. Table 3 presents the model applications' results. A t-test was used to establish the lowest AIC among the available variants. Only valid models characterized by statistically significant non-zero coefficients were selected.

Table 3. Values of coefficients in the EGARCH model				
Index	**Coefficient**			
	α_0	α	γ	β
AEX	−6.9904	−2.5952	−1.0215	0.1698
ASX	−11.91087	−1.528558	−2.144349	−0.143220
ATHEX	−10.9941	−0.9424	0.2763	−0.1416
ATX	−6.5132	0.8536	−0.1710	0.4229
BEL 20	−12.3812	2.0626	0.1089	0.0675
BELEX 15	−5.2456	1.2281	−0.1891	0.6438
BET	−18.9049	1.2976	0.1398	−0.7248
BIRS	−2.4896	−0.8460	0.4451	0.7241
BOVESPA	−11.0105	0.4064	−0.3520	−0.0465
BUX	−1.8772	0.0518	−0.1734	0.8136
CAC 40	−12.0017	1.6260	−0.2896	0.0044
CROBEX	−6.492775	−1.8319	0.5753	0.3249
DAX 40	−7.2118	0.4647	−0.2558	0.3532
FTSE MIB	−7.4833	1.1579	0.2281	0.3736
FTSE 250	−6.0266	0.1495	0.0649	0.4344
HEX	−9.4523	1.3747	−0.2745	0.2241
IBEX	−11.3658	0.5350	−0.1417	−0.0262
ICEX	−7.0494	−2.7670	−1.4680	0.1451
ISEQ	−8.8804	0.3978	0.2020	0.1567
JTOPI	−7.7923	−0.0879	0.3807	0.2444
NIKKEI	−1.6992	−0.8203	−0.1763	0.7804
OMX COPENHAGEN 20	−7.2326	0.6086	−0.0687	0.3476
OMX RIGA	−7.7407	2.9426	−0.0495	0.5074
OMX STOCKHOLM	−10.3370	0.2039	−0.0099	0.0275
OMX TALLINN	−0.9988	−0.5611	−0.2263	0.8702
OMX VILNIUS	−20.5940	1.5520	−0.3629	−0.5517
OSEAX	−18.7627	0.6680	−0.0336	−0.6510
PSI 20	−2.5848	−0.8671	−0.4459	0.6981
PX	−0.3326	−0.3977	−0.3205	0.9368
RTS	−7.4643	0.9749	−0.8891	0.2004
SAX	−11.9083	0.2607	0.2250	0.0093
SBITOP	−1.0844	−0.4481	−0.5313	0.8591
SHC	−6.3626	−2.1042	−0.6984	0.2665
SMI	−9.0473	−1.7263	−1.5094	0.0767
SOFIX	0.7690	−0.1511	−0.1977	1.0594
SP 500	−7.1488	0.6093	−0.6197	0.3503
STI	−1.8058	0.0767	−0.5468	0.8442
TADAWUL 30	−4.7086	−1.4818	0.0898	0.4073
WIG20	−11.3209	0.63511	0.2098	−0.0850
XU 100	−2.1774	0.3357	−0.2019	0.8093

The term α from relation 10 represents how conflict-related news volume affects future index return volatility. A value greater than zero indicates a positive relationship between the past and present variance of the observed return on the indices ATX, BEL 20, BELEX 15, BET, BOVESPA, BUX, CAC 40, DAX 40, FTSE MIB, FTSE 250, HEX, IBEX, ISEQ, OMX Copenhagen 20, OMX Riga, OMX Stockholm, OMX Vilnius, OSEAX, RTS, SAX, SP 500, WIG20, and XU 100. The volatility increases as the variance shock's magnitude increases. The phrase γ reveals the conflict-induced shock's nature and impact on the index return volatility. A negative value indicates leverage, meaning that more volatility will be caused by bad news than by good news of equal magnitude (AEX, ATX, BELEX 15, BOVESPA, BUX, CAC 40, DAX 40, HEX, IBEX, ICEX, NIKKEI, OMX Copenhagen 20, OMX Riga, OMX Stockholm, OMX Tallinn, OMX Vilnius, OSEAX, PSI 20, PX, RTS, SBITOP, SHC, SMI, SOFIX, SP 500, and XU 100). The β coefficient has rich informational content. If the coefficient is statistically significant and negative, lower returns produce higher volatility than higher returns of the same magnitude (Table 3).

5. Discussion

An escalation in market volatility marked the onset of the Russia-Ukraine conflict, initiated by news of Russian troop advancement and subsequent bombings. As noted by Yousafet al. (2022a), some markets responded more swiftly than others, a finding echoed by our analysis of volatility dynamics. Markets closer to Ukraine, such as Hungary, Poland, Serbia, Bosnia and Herzegovina, and the Czech Republic, reacted days before the official conflict began, potentially in response to early reports of troop mobilization.

Post-conflict, stock markets in Finland, Latvia, Estonia, Romania, Bulgaria, Greece, and Serbia, reacted rapidly and intensely, revealing high volatility followed by a stabilization phase. As investor confidence increased, believing NATO would not directly intervene in the conflict (Kumari et al., 2023), positive post-event results were observed.

Our results affirm the findings of Neely (2022) that war impacts on markets depend on geographical proximity. Markets situated further away, such as Brazil, Australia, South Africa, and Iceland, showed significantly lower volatility. A global negative impact on stock markets was noted owing to the Russia-Ukraine conflict, with European markets depreciating notably, while others showed lesser reactions. Our findings indicate that the Russia-Ukraine conflict had a global negative impact on stock markets. As per the regional analysis, although European markets in particular depreciated, other markets reacted much less. A similar but more accentuated behavior was identified by Chortane and Pandey (2022), in the behavior of the currencies from the Pacific, the Middle East and Africa against the American dollar after the start of the invasion of Ukraine.

Our results also indicated a significantly lower volatility in larger markets, regardless of geographical distance. Markets in the US, China, Japan, the UK, and Germany experienced lower volatilities during the analyzed period, supplementing findings by Abbassi et al. (2023) and Boubaker et al. (2022). The imposed sanctions on Russia by NATO countries and Moscow's subsequent response could be a possible explanation. Turkey exhibited a unique behavior, characterized by low volatility in the initial phase, followed by increased and sustained volatility.

In the post-event period, Poland, Denmark, and Portugal showed positive cumulative abnormal returns (CARs), with Poland being in close proximity to the conflict (Kumari et al., 2023). We confirm Poland's case, but disagree with the swift recovery claimed by Kumari et al., as we found that Poland experienced high volatility throughout the period, potentially owing to a large influx of Ukrainian refugees. Our network analysis further indicated a war-induced shift in connections among EU stock markets, clustering them according to geographical positions.

Our study included the Baltic states, with close economic and financial ties, which displayed similar responses—high volatility followed by stabilization. On the contrary, Scandinavian countries —Denmark, Sweden, and Norway—exhibited a delayed and less volatile response to the onset of the conflict, as compared to their counterparts closer to Ukraine. Finland, however, marked higher volatility, potentially due to its extensive border with Russia.

Following the war-induced crash in stock market indices, the markets' reaction to negative news, sanctions, and governmental responses varied in intensity. Maximum volatility was observed in early March. On 9 March 2022, the Netherlands, Belgium, Romania, France, Germany, Italy, the UK, Finland, Spain, Estonia, Switzerland, and Bulgaria reached their peak volatility values, with Russia experiencing the highest volatility. From March 2 to 16, 2022, 21 of the countries analyzed registered their maximum volatility. Following this peak, most markets trended towards lower volatility.

These varying responses across developed markets, both temporally and in magnitude, hint at a potential influence of their economic relations with the warring countries. The war triggered an immediate response in asset prices, yet as more information became available, markets corrected, mirroring the reactions seen during the initial wave of the COVID-19 pandemic (Zheng et al., 2021).

6. Conclusions and future research directions

In conclusion, the uncertainty resulting from political, economic, and financial instability, geographical proximity, and sanctions imposed on Russia led to negative reactions in the stock markets during the period analyzed. The Russia-Ukraine conflict, occurring amid global recovery from the COVID-19 pandemic, introduced another layer of shock to the capital markets. We conducted a volatility analysis to identify its impact on stock markets, filling a void in the literature by investigating the war's effects on volatility in 40 countries. We found that the conflict resulted in negative shocks in the stock indices analyzed. Our results allow for comparisons between the volatility recorded during the conflict and other political or similar events that affected the world economy and specific geographic areas. Military events affect long-term economic growth worldwide. Military wars have significantly influenced all political and military events since the World War II. This study has implications for shareholders, investment funds, analysts, capital markets authorities, and governments, all invested in understanding dynamics to make informed investment decisions amid the uncertainty fueled by the Russia-Ukraine conflict.

Factors such as refugee movements from Ukraine, particularly to Poland, Hungary, Romania, Moldova, and the Baltic states, may have influenced capital market reactions. The volatility in countries imposing sanctions could potentially be explained by these measures. We earmark these hypotheses for future research. We propose further research into a differentiated analysis of sectoral indices, considering some sectors like the energy sector appreciated post-conflict.

Due to the recentness of the war, limited literature was available for reference. Still, our work is likely to align with contemporaneous studies. As the 2022 military events are a continuation of those from 2014, a comparative analysis of volatility between these two periods could be insightful.

The main limitations come from the uncertainty of the war between Russia and Ukraine. Lack of information and inaccuracies may have influenced the obtained results. No explanations were found for the atypical behavior of some markets, such as Turkey and China, which presents directions for future work. The measures, sanctions, and countermeasures adopted by belligerent states or NATO members contributed to the emergence of some volatility that affected certain markets during the analyzed period. Last but not least, the effect of news and selected keywords depends on many control variables, aspects that can have important implications.

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Appendix 1. Daily logarithmic return descriptive statistics

Index	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Probability
AEX	−0.0006	−0.0008	0.0120	−0.0160	0.0055	−0.2340	3.4718	0.9570	0.6197
ASX	−0.0005	−0.001	0.0087	−0.0171	0.0046	−0.8504	4.7066	12.578	0.0019
ATHEX	0.0001	0.0015	0.0110	−0.0242	0.0068	−1.1114	4.9491	18.936	0.0001
ATX	−0.0007	−0.0004	0.0138	−0.0292	0.0078	−1.0037	5.0085	17.472	0.0002
BEL 20	−0.0006	−0.0015	0.0123	−0.0154	0.0044	−0.2116	5.0064	9.1108	0.0105
BELEX 15	0.0000	0.0000	0.0079	−0.0097	0.0032	−0.1279	4.2380	3.4625	0.1771
BET	−0.0004	−0.0001	0.0116	−0.0247	0.0066	−0.9616	5.3021	19.496	0.0001
BIRS	0.0009	0.0002	0.0272	−0.0081	0.0060	2.1475	10.088	148.81	0.0000
BOVESPA	0.0001	0.0005	0.0136	−0.0138	0.0067	−0.0377	2.2134	1.3529	0.5084
BUX	−0.0006	0.0005	0.0133	−0.0257	0.0078	−0.7939	4.3123	9.1938	0.0101
CAC 40	−0.0004	−0.0001	0.0112	−0.0216	0.0056	−0.9863	5.4831	21.790	0.0000
CROBEX	−0.0003	0.0004	0.0075	−0.0118	0.0034	−1.0601	5.1295	19.566	0.0001
DAX 40	−0.0006	−0.0003	0.0112	−0.0213	0.0057	−0.7044	5.2215	14.992	0.0006
FTSE MIB	−0.0007	0.0003	0.0109	−0.0275	0.0064	−1.3277	7.4102	57.418	0.0000
FTSE 250	−0.0010	−0.0013	0.0134	−0.0151	0.0056	0.1497	3.2769	0.3602	0.8352
HEX	−0.0007	−0.0007	0.0128	−0.0232	0.0058	−0.7290	6.0163	24.318	0.0000
IBEX	−0.0002	−0.0006	0.0106	−0.0189	0.0052	−0.5879	5.0094	11.744	0.0028
ICEX	−0.0008	−0.0008	0.0127	−0.0124	0.0054	0.1271	2.8555	0.1853	0.9115
ISEQ	−0.0007	−0.0011	0.0134	−0.0257	0.0070	−0.6907	4.6858	10.293	0.0058
JTOPI	−0.0002	0.0009	0.0114	−0.0165	0.0057	−0.3959	3.2421	1.4853	0.4759

(*Continued*)

(Continued)

Index	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Probability
NIKKEI	−0.0003	−0.0005	0.0128	−0.0138	0.0054	0.2668	3.1830	0.6894	0.7084
OMX Copenhagen 20	−0.0003	0.0008	0.0124	−0.0148	0.0066	−0.4076	2.3806	2.2715	0.3212
OMX RIGA	−0.0003	−0.0004	0.0256	−0.0247	0.0068	−0.0015	8.5943	67.809	0.0000
OMX Stockholm	−0.0008	−0.0004	0.0107	−0.0151	0.0058	−0.0251	2.6317	0.2994	0.8610
OMX Tallinn	−0.0006	−0.0005	0.0081	−0.0140	0.0046	−0.5252	3.6585	3.3296	0.1892
OMX Vilnius	−0.0001	0.0001	0.0051	−0.0130	0.0031	−1.5273	7.4196	62.537	0.0000
OSEAX	0.0001	−0.0001	0.0085	−0.0118	0.0049	−0.0960	2.2237	1.3854	0.5002
PSI 20	0.0000	−0.0005	0.0105	−0.0126	0.0046	−0.0157	3.1647	0.0609	0.9700
PX	−0.0006	−0.0005	0.0084	−0.0114	0.0050	−0.2866	2.2874	1.8124	0.4041
RTS	−0.0041	−0.0010	0.0440	−0.1217	0.0246	−2.6511	13.499	282.45	0.0000
SAX	−0.0007	0.0000	0.0059	−0.0111	0.0031	−1.0979	5.0058	19.164	0.0001
SBITOP	−0.0008	−0.0003	0.0164	−0.0178	0.0057	−0.0306	4.4299	4.4382	0.1087
SHC	−0.0008	−0.0011	0.0104	−0.0106	0.0046	−0.1338	2.6354	0.4261	0.8081
SMI	−0.0008	−0.0006	0.0116	−0.0118	0.0046	−0.0996	3.6644	1.0424	0.5938
SOFIX	−0.0003	−0.0005	0.0079	−0.0139	0.0037	−0.6396	5.4405	16.450	0.0003
SP 500	−0.0008	−0.0021	0.0156	−0.0146	0.0068	0.4470	2.6931	1.9356	0.3799
STI	0.0002	0.0001	0.0086	−0.0080	0.0039	−0.0194	2.4452	0.6701	0.7153
TADAWUL 30	−0.0005	0.0000	0.0175	−0.0205	0.0077	−0.1788	3.3791	0.5773	0.7493
WIG20	−0.0010	0.0009	0.0149	−0.0168	0.0079	−0.0825	2.3090	1.0934	0.5788
XU 100	0.0040	0.0039	0.0230	−0.0107	0.0078	0.1158	2.3281	1.0944	0.5786

Appendix 2. ADF results

ADF	t-Statistic	Probability*	ADF	t-Statistic	Probability*
AEX	−11.2125	0.0000	ASX	−7.0277.	0.0000
1% level	−3.5683		1% level	−3.5744.	
5% level	−2.9211		5% level	−2.9238	
10% level	−2.5985		10% level	−2.5999	
ATHEX	−8.3036	0.0000	ATX	−8.4506	0.0000
1% level	−3.5713		1% level	−3.5683	
5% level	−2.9224		5% level	−2.9211	
10% level	−2.5992		10% level	−2.5985	
BEL 20	−8.7644	0.0000	BELEX 15	−5.8366	0.0000
1% level	−3.5713		1% level	−3.5777	
5% level	−2.9224		5% level	−2.9251	
10% level	−2.5992		10% level	−2.6006	
BET	−9.9057	0.0000	BIRS	−22.1583	0.0001
1% level	−3.5713		1% level	−3.5683	
5% level	−2.9224		5% level	−2.9211	
10% level	−2.5992		10% level	−2.5985	
BOVESPA	−14.8019	0.0000	BUX	−7.7699	0.0000
1% level	−3.5683		1% level	−3.5713	
5% level	−2.9211		5% level	−2.9224	
10% level	−2.5985		10% level	−2.5992	
CAC 40	−10.5630	0.0000	CROBEX	−8.4091	0.0000
1% level	−3.5683		1% level	−3.5713	
5% level	−2.9211		5% level	−2.9224	
10% level	−2.5985		10% level	−2.5992	
DAX 40	−10.0711	0.0000	FTSE MIB	−10.3509	0.0000
1% level	−3.5683		1% level	−3.5683	
5% level	−2.9211		5% level	−2.9211	
10% level	−2.5985		10% level	−2.5985	
FTSE 250	−11.1700	0.0000	HEX	−8.9629	0.0000
1% level	−3.5683		1% level	−3.5713	
5% level	−2.9211		5% level	−2.9224	
10% level	−2.5985		10% level	−2.5992	
IBEX	−7.6068	0.0000	ICEX	−8.2635	0.0000
1% level	−3.5744		1% level	−3.5713	
5% level	−2.9237		5% level	−2.9224	
10% level	−2.5999		10% level	−2.5992	
ISEQ	−10.6396	0.0000	JTOPI	−13.8053	0.0000
1% level	−3.5683		1% level	−3.5683	

(Continued)

ADF	t-Statistic	Probability*	ADF	t-Statistic	Probability*
5% level	−2.9211		5% level	−2.9211	
10% level	−2.5985		10% level	−2.5985	
NIKKEI	−7.2283	0.0000	OMX COPENHAGEN 20	−10.4174	0.0000
1% level	−3.5744		1% level	−3.5713	
5% level	−2.9237		5% level	−2.9224	
10% level	−2.5999		10% level	−2.5992	
OMX RIGA	−7.8353	0.0000	OMX STOCKHOLM	−8.4159	0.0000
1% level	−3.5744		1% level	−3.5713	
5% level	−2.9237		5% level	−2.9224	
10% level	−2.5999		10% level	−2.5992	
OMX TALLINN	−9.4194	0.0000	OMX VILNIUS	−8.3250	0.0000
1% level	−3.5713		1% level	−3.5683	
5% level	−2.9224		5% level	−2.9211	
10% level	−2.5992		10% level	−2.5985	
OSEAX	−9.2137	0.0000	PSI 20	−7.6929	0.0000
1% level	−3.5713		1% level	−3.5713	
5% level	−2.9224		5% level	−2.9224	
10% level	−2.5992		10% level	−2.5992	
PX	−5.2077	0.0001	RTS	−8.6673	0.0000
1% level	−3.5885		1% level	−3.5811	
5% level	−2.9297		5% level	−2.9266	
10% level	−2.6030		10% level	−2.6014	
SAX	−8.7146	0.0000	SBITOP	−7.7351	0.0000
1% level	−3.5713		1% level	−3.5713	
5% level	−2.9224		5% level	−2.9224	
10% level	−2.5992		10% level	−2.5992	
SHC	−8.5262	0.0000	SMI	−7.2421	0.0000
1% level	−3.5777		1% level	−3.5744	
5% level	−2.9251		5% level	−2.9237	
10% level	−2.6006		10% level	−2.5999	
SOFIX	−9.5536	0.0000	SP 500	−7.4251	0.0000
1% level	−3.5683		1% level	−3.5744	
5% level	−2.9211		5% level	−2.9237	
10% level	−2.5985		10% level	−2.5999	
STI	−8.9980	0.0000	TADAWUL 30	−8.4627	0.0000
1% level	−3.5683		1% level	−3.5744	

(Continued)

(Continued)

ADF	t-Statistic	Probability*	ADF	t-Statistic	Probability*
5% level	−2.9211		5% level	−2.9237	
10% level	−2.5985		10% level	−2.5999	
WIG20	−10.5395	0.0000	XU 100	−12.340	0.0000
1% level	−3.5683		1% level	−3.5683	
5% level	−2.9211		5% level	−2.9211	
10% level	−2.5985		10% level	−2.5985	

ADF: Augmented Dickey—Fuller

*Author's calculations using EVIEWS 10.

Appendix 3. Granger results

Null Hypothesis	F-Statistic	Probability	Causality direction
GSVI does not Granger Cause AEX	4.1668	0.0219	Unidirectional
AEX does not Granger Cause GT	0.5681	0.5706	No causality
GSVI does not Granger Cause ASX	0.4021.	0.5290.	No causality
ASX does not Granger Cause GT	0.2678	0.6072	No causality
GSVI does not Granger Cause ATHEX	3.7170	0.0598	No causality
ATHEX does not Granger Cause GT	0.3383	0.5635	No causality
GSVI does not Granger Cause ATX	4.1561	0.0221	Unidirectional
ATX does not Granger Cause GT	0.4701	0.6279	No causality
GSVI does not Granger Cause BEL 20	7.42023	0.0004	Unidirectional
BEL 20 does not Granger Cause GT	0.3953	0.6758	No causality
GSVI does not Granger Cause BELEX 15	1.2424	0.2706	No causality
BELEX 15 does not Granger Cause GT	0.5844	0.4483	No causality
GSVI does not Granger Cause BET	6.3543	0.0037	Unidirectional
BET does not Granger Cause GT	0.5281	0.5933	No causality
GSVI does not Granger Cause BIRS	0.1576	0.9242	No causality
BIRS does not Granger Cause GT	0.8611	0.4688	No causality
GSVI does not Granger Cause BOVESPA	0.1037	0.7488	No causality

(Continued)

Null Hypothesis	F-Statistic	Probability	Causality direction
BOVESPA does not Granger Cause GT	0.0896	0.7659	No causality
GSVI does not Granger Cause BUX	4.9885	0.0110	Unidirectional
BUX does not Granger Cause GT	0.3552	0.7030	No causality
GSVI does not Granger Cause CAC 40	7.8832	0.0012	Unidirectional
CAC 40 does not Granger Cause GT	0.1441	0.8662	No causality
GSVI does not Granger Cause CROBEX	3.3301	0.0448	Unidirectional
CROBEX does not Granger Cause GT	0.4194	0.6600	No causality
GSVI does not Granger Cause DAX 40	12.2318	6.0E−05	Unidirectional
DAX 40 does not Granger Cause GT	0.0334	0.9672	No causality
GSVI does not Granger Cause FTSE MIB	10.7144	0.0002	Unidirectional
FTSE MIB does not Granger Cause GT	0.3423	0.7120	No causality
GSVI does not Granger Cause FTSE 250	6.8427	0.0025	Unidirectional
FTSE 250 does not Granger Cause GT	0.0627	0.9392	No causality
GSVI does not Granger Cause HEX	9.5284	0.0004	Unidirectional
HEX does not Granger Cause GT	0.5669	0.5713	No causality
GSVI does not Granger Cause IBEX	9.7573	0.0003	Unidirectional
IBEX does not Granger Cause GT	1.1052	0.3399	No causality
GSVI does not Granger Cause ICEX	0.7920	0.3779	No causality
ICEX does not Granger Cause GT	0.0026	0.9589	Unidirectional
GSVI does not Granger Cause ISEQ	11.9722	7.0E−05	Unidirectional
ISEQ does not Granger Cause GT	0.4629	0.6324	No causality
GSVI does not Granger Cause JTOPI	0.0003	0.9844	No causality
JTOPI does not Granger Cause GT	0.0612	0.8056	No causality
GSVI does not Granger Cause NIKKEI	3.7009	0.0189	Unidirectional

(Continued)

(Continued)

Null Hypothesis	F-Statistic	Probability	Causality direction
NIKKEI does not Granger Cause GT	1.0221	0.3925	No causality
GSVI does not Granger Cause OMX COPENHAGEN 20	2.8774	0.0963	No causality
OMX COPENHAGEN_20 does not Granger Cause GT	0.0769	0.7826	No causality
GSVI does not Granger Cause OMX RIGA	7.5184	0.0015	Unidirectional
OMX RIGA does not Granger Cause GT	0.0879	0.9160	No causality
GSVI does not Granger Cause OMX STOCKHOLM	4.8444	0.0124	Unidirectional
OMX STOCKHOLM does not Granger Cause GT	0.5767	0.5658	No causality
GSVI does not Granger Cause OMX TALLINN	1.9460	0.1547	No causality
OMX TALLINN does not Granger Cause GT	1.5455	0.2243	No causality
GSVI does not Granger Cause OMX VILNIUS	7.4180	0.0016	Unidirectional
OMX VILNIUS does not Granger Cause GT	0.9191	0.4062	No causality
GSVI does not Granger Cause OSEAX	0.5422	0.4651	No causality
OSEAX does not Granger Cause GT	1.2744	0.2645	No causality
GSVI does not Granger Cause PSI 20	3.2654	0.0474	Unidirectional
PSI 20 does not Granger Cause GT	0.3571	0.7016	No causality
GSVI does not Granger Cause PX	0.1544	0.6961	No causality
PX does not Granger Cause GT	0.2557	0.6154	No causality
GSVI does not Granger Cause RTS	12.8977	4.0E−05	Unidirectional
RTS does not Granger Cause GT	0.0196	0.9805	No causality
GSVI does not Granger Cause SAX	0.6075	0.4395	No causality
SAX does not Granger Cause GT	0.0346	0.8531	No causality
GSVI does not Granger Cause SBITOP	0.0514	0.8215	No causality
SBITOP does not Granger Cause GT	0.4330	0.5137	No causality

(*Continued*)

Null Hypothesis	F-Statistic	Probability	Causality direction
GSVI does not Granger Cause SHC	0.3339	0.5662	No causality
SHC does not Granger Cause GT	0.1293	0.7208	No causality
GSVI does not Granger Cause SMI	3.8183	0.0294	Unidirectional
SMI does not Granger Cause GT	0.7621	0.4726	No causality
GSVI does not Granger Cause SOFIX	5.6488	0.0065	Unidirectional
SOFIX does not Granger Cause GT	0.1149	0.8917	No causality
GSVI does not Granger Cause SP 500	2.0771	0.1371	No causality
SP 500 does not Granger Cause GT	0.3759	0.6888	No causality
GSVI does not Granger Cause STI	0.2052	0.6525	No causality
STI does not Granger Cause GT	0.3694	0.5462	No causality
GSVI does not Granger Cause TADAWUL 30	1.2199	0.2750	No causality
TADAWUL 30 does not Granger Cause GT	0.1391	0.7108	No causality
GSVI does not Granger Cause WIG20	0.7916	0.3780	No causality
WIG20 does not Granger Cause GT	0.0126	0.9110	No causality
GSVI does not Granger Cause XU 100	0.0002	0.9869	No causality
XU 100 does not Granger Cause GT	0.0271	0.8699	No causality

Source: * Indicates significance at the 1 and 5% levels. Authors' calculations using EVIEWS.

Appendix 4. VAR lag order selection criteria

Index	Lag	LogL	LR	FPE	AIC	SC	HQ
AEX	2	−72.1985	8.729695	0.0983*	3.3550*	3.7411	3.5015
ASX	1	−65.4824	20.26937*	0.6741*	2.9784*	3.2123*	3.0668*
ATHEX	1	−90.3012	14.69496*	0.1746*	3.9306*	4.1623*	4.0185*
ATX	2	−87.4799	11.83739*	0.1834*	3.9787*	4.3648	4.1252*
BEL 20	2	−58.8863	18.51113*	0.0571*	2.8116*	3.1977*	2.9581*
BELEX 15	1	−48.6310	20.26255*	0.0318*	2.2298*	2.4614*	2.3177*
BET	2	−78.6244	12.25451*	0.1278*	3.6173*	4.0034	3.7638*
BIRS	3	−55.7877	8.762414	0.0594*	2.8484*	3.3889	3.0535
BOVESPA	1	−93.0100	16.44445*	0.1951*	4.0412*	4.2728*	4.1291*
BUX	2	−90.6313	8.181011	0.2086*	4.1074*	4.4934	4.2538
CAC 40	2	−64.6114	13.31190*	0.0721*	3.0453*	3.4314	3.1918*
CROBEX	2	−50.1960	7.261272	0.0400*	2.4569*	2.8430	2.6034
DEX 40	2	−56.3300	20.36914*	0.0514*	2.7073*	3.0934*	2.8538*
FTSE MIB	2	−71.0267	17.26063*	0.0937*	3.3072*	3.6932*	3.4536*
FTSE 250	2	−77.8506	12.20921*	0.1238*	3.5857*	3.9718	3.7322*
HEX	2	−71.2234	18.64927*	0.0945*	3.3152*	3.7013*	3.4617*
IBEX	2	−63.6564	20.22419*	0.0693*	3.0063*	3.3924*	3.1528*
ICEX	1	−86.3979	10.45902*	0.1489*	3.7713*	4.0029	3.8592*
ISEQ	2	−90.5443	17.36646*	0.2079*	4.1038*	4.4899*	4.2503*
JTOPI	1	−89.2291	18.55082*	0.1672*	3.8869*	4.1185*	3.9747*
NIKKEI	3	−64.5535	10.25288*	0.0849*	3.2062*	3.7467	3.4113
OMX Copenhagen 20	1	−85.6507	19.66714*	0.1444*	3.7408*	3.9724*	3.8287*
OMX Riga	2	−82.7905	10.73672*	0.1515*	3.7873*	4.1734	3.9338*
OMX Stockholm	2	−78.5197	9.353702	0.1272*	3.6130*	3.9991	3.7595
OMX Tallinn	2	−62.6362	13.74771*	0.0665*	2.9647*	3.3508	3.1112*
OMX Vilnius	2	−43.29337	14.44153*	0.0302*	2.1752*	2.5613*	2.3217*
OSEAX	1	−76.1986	23.23401*	0.0982*	3.3550*	3.5866*	3.4429*
PSI 20	2	−58.1024	10.26002*	0.0553*	2.7796*	3.1657	2.9261*
PX	1	−77.9234	19.00575*	0.1053*	3.4254*	3.6570*	3.5133*
RTS	2	−115.470	7.862703	0.8034*	5.4552*	5.8527	5.6041
SAX	1	−52.1380	16.78114*	0.0367*	2.3729*	2.6046*	2.4608*
SBITOP	1	−76.9024	18.54938*	0.1010*	3.3837*	3.6154*	3.4716*
SHC	1	−78.5544	10.69530*	0.1252*	3.5980*	3.8342	3.6869*
SMI	2	−68.4830	8.948500	0.0845*	3.2033*	3.5894	3.3498
SOFIX	2	−51.7885	11.94559*	0.0427*	2.5219*	2.9080	2.6684*
SP 500	2	−81.8450	7.453548	0.1457*	3.7487*	4.1348	3.8952

(Continued)

Index	Lag	LogL	LR	FPE	AIC	SC	HQ
STI	1	−54.9033	16.42851*	0.0411*	2.4858*	2.7175*	2.5737*
TADAWUL 30	1	−87.4961	9.872251*	0.1686*	3.8956*	4.1295	3.9840
WIG20	1	−92.9508	25.09179*	0.1946*	4.0388*	4.2704*	4.1266*
XU 100	1	−89.9636	9.419330	0.1722*	3.9168*	4.1485	4.0047

*indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.
Author's calculations using EVIEWS.

Appendix 5. Johansen Cointegration Test

	Hypothesized No. of CE(s)	Unrestricted Cointegration Rank Test (Trace)				Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				Cointegrating Equation(s): Log likelihood
		Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**	
AEX-GSVI	None *	0.2981	23.767	15.495	0.0023	0.2981	17.344	14.265	0.0158	−74.078
	At most 1 *	0.1229	6.4228	3.8415	0.0113	0.1229	6.4228	3.8415	0.0113	
ASX-GSVI	None *	0.3584	31.883	15.495	0.0001	0.3584	22.189	14.265	0.0023	−71.231
	At most 1 *	0.1762	9.6942	3.8415	0.0018	0.1762	9.694	3.8415	0.0018	
ATHEX-GSVI	None *	0.4127	39.168	15.495	0.0000	0.4127	26.608	14.265	0.0004	−93.617
	At most 1 *	0.2221	12.560	3.8415	0.0004	0.2221	12.560	3.8415	0.0004	
ATX-GSVI	None *	0.3627	27.235	15.495	0.0006	0.3627	22.079	14.265	0.0024	−88.348
	At most 1 *	0.0999	5.1557	3.8415	0.0232	0.0999	5.1557	3.8415	0.0232	
BEL20-GSVI	None *	0.3322	25.759	15.495	0.0010	0.3322	19.788	14.265	0.0061	−61.195
	At most 1 *	0.1147	5.9706	3.8415	0.0145	0.1147	5.9706	3.8415	0.0145	
BELEX 15-GSVI	None *	0.3444	29.578	15.495	0.0002	0.3444	21.113	14.265	0.0036	−54.944
	At most 1 *	0.1557	8.4652	3.8415	0.0036	0.1557	8.4652	3.8415	0.0036	
BET-GSVI	None *	0.2439	20.431	15.495	0.0083	0.2439	13.698	14.265	0.0613	−80.130
	At most 1 *	0.1284	6.7332	3.8415	0.0095	0.1284	6.7332	3.8415	0.0095	
BIRS-GSVI	None *	0.3421	28.324	15.495	0.0004	0.3421	20.094	14.265	0.0054	−52.721
	At most 1 *	0.1576	8.2295	3.8415	0.0041	0.1576	8.2295	3.8415	0.0041	
BOVESPA-GSVI	None *	0.2456	26.450	15.495	0.0008	0.2456	14.093	14.265	0.0532	−98.819
	At most 1 *	0.2190	12.356	3.8415	0.0004	0.2190	12.356	3.8415	0.0004	
BUX-GSVI	None *	0.2736	25.415	15.495	0.0012	0.2736	15.666	14.265	0.0298	−94.744
	At most 1 *	0.1804	9.7492	3.8415	0.0018	0.1804	9.7492	3.8415	0.0018	

(*Continued*)

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CAC 40-GSVI	None *	0.2685	22.464	15.495	0.0038	0.2685	15.320	14.265	0.0339	−67.225
	At most 1 *	0.1357	7.1441	3.8415	0.0075	0.1357	7.1441	3.8415	0.0075	
CROBEX-GSVI	None *	0.3328	28.631	15.495	0.0003	0.3328	19.826	14.265	0.0060	−52.870
	At most 1 *	0.1645	8.8058	3.8415	0.0030	0.1645	8.8058	3.8415	0.0030	
DAX 40-GSVI	None *	0.2348	20.146	15.495	0.0092	0.2348	13.115	14.265	0.0753	−56.371
	At most 1 *	0.1337	7.0304	3.8415	0.0080	0.1337	7.0304	3.8415	0.0080	
FTSE MIB-GSVI	None *	0.3028	24.912	15.495	0.0014	0.3028	17.675	14.265	0.0139	−74.397
	At most 1 *	0.1373	7.2369	3.8415	0.0071	0.1373	7.2369	3.8415	0.0071	
FTSE 250-GSVI	None *	0.2778	23.800	15.495	0.0022	0.2778	15.944	14.265	0.0269	−78.893
	At most 1 *	0.1481	7.8559	3.8415	0.0051	0.1481	7.8559	3.8415	0.0051	
HEX-GSVI	None *	0.2582	21.530	15.495	0.0054	0.2582	14.636	14.265	0.0437	−72.417
	At most 1 *	0.1312	6.8934	3.8415	0.0086	0.1312	6.8934	3.8415	0.0086	
IBEX-GSVI	None *	0.2935	25.825	15.495	0.0010	0.2935	17.026	14.265	0.0178	−66.970
	At most 1 *	0.1644	8.7984	3.8415	0.0030	0.1644	8.7984	3.8415	0.0030	
ICEX-GSVI	None *	0.3851	30.333	15.495	0.0002	0.3851	24.316	14.265	0.0010	−87.606
	At most 1 *	0.1134	6.0179	3.8415	0.0142	0.1134	6.0179	3.8415	0.0142	
ISEQ-GSVI	None *	0.2854	21.884	15.495	0.0047	0.2854	16.463	14.265	0.0221	−89.764
	At most 1 *	0.1047	5.4208	3.8415	0.0199	0.1047	5.4208	3.8415	0.0199	
JTOPI-GSVI	None *	0.3341	31.684	15.495	0.0001	0.3341	20.331	14.265	0.0049	−94.277
	At most 1 *	0.2031	11.353	3.8415	0.0008	0.2031	11.353	3.8415	0.0008	
NIKKEI-GSVI	None *	0.3045	23.964	15.495	0.0021	0.3045	17.429	14.265	0.0153	−64.893
	At most 1 *	0.1273	6.5349	3.8415	0.0106	0.1273	6.5349	3.8415	0.0106	

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OMX COPENHAGEN 20-GSVI	None *	0.4420	39.452	15.495	0.0000	0.4420	29.171	14.265	0.0001	−90.647
	At most 1 *	0.1859	10.281	3.8415	0.0013	0.1859	10.281	3.8415	0.0013	
OMX Riga-GSVI	None *	0.3192	29.778	15.495	0.0002	0.3192	18.843	14.265	0.0088	−87.205
	At most 1 *	0.2000	10.935	3.8415	0.0009	0.2000	10.935	3.8415	0.0009	
OMX Stockholm-GSVI	None *	0.2466	20.962	15.495	0.0068	0.2466	13.875	14.265	0.0575	−79.591
	At most 1 *	0.1347	7.0871	3.8415	0.0078	0.1347	7.0871	3.8415	0.0078	
OMX Tallinn-GSVI	None *	0.3216	29.043	15.495	0.0003	0.3216	19.015	14.265	0.0082	−65.509
	At most 1 *	0.1851	10.028	3.8415	0.0015	0.1851	10.028	3.8415	0.0015	
OMX Vilnius-GSVI	None *	0.2800	25.809	15.495	0.0010	0.2800	16.094	14.265	0.0254	−47.635
	At most 1 *	0.1799	9.7151	3.8415	0.0018	0.1799	9.7151	3.8415	0.0018	
OSEAX-GSVI	None *	0.3995	38.013	15.495	0.0000	0.3995	25.501	14.265	0.0006	−81.332
	At most 1 *	0.2214	12.511	3.8415	0.0004	0.2214	12.511	3.8415	0.0004	
PSI 20-GSVI	None *	0.2731	23.641	15.495	0.0024	0.2731	15.626	14.265	0.0303	−61.667
	At most 1 *	0.1509	8.0152	3.8415	0.0046	0.1509	8.0152	3.8415	0.0046	
PX-GSVI	None *	0.3966	43.658	15.495	0.0000	0.3966	25.256	14.265	0.0006	−84.267
	At most 1 *	0.3079	18.401	3.8415	0.0000	0.3079	18.401	3.8415	0.0000	
RTS-GSVI	None *	0.3155	28.381	15.495	0.0004	0.3155	17.438	14.265	0.0152	−119.602
	At most 1 *	0.2117	10.943	3.8415	0.0009	0.2117	10.943	3.8415	0.0009	
SAX-GSVI	None *	0.4239	43.864	15.495	0.0000	0.4239	27.572	14.265	0.0002	−58.386
	At most 1 *	0.2781	16.292	3.8415	0.0001	0.2781	16.292	3.8415	0.0001	
SBITOP-GSVI	None *	0.3956	40.094	15.495	0.0000	0.3956	25.175	14.265	0.0007	−82.835
	At most 1 *	0.2580	14.919	3.8415	0.0001	0.2580	14.919	3.8415	0.0001	

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SHC-GSVI	None *	0.3909	36.373	15.495	0.0000	0.3909	23.800	14.265	0.0012	−83.550
	At most 1 *	0.2304	12.572	3.8415	0.0004	0.2304	12.572	3.8415	0.0004	
SMI-GSVI	None *	0.2780	25.556	15.495	0.0011	0.2780	15.962	14.265	0.0267	−72.460
	At most 1 *	0.1778	9.5937	3.8415	0.0020	0.1778	9.5937	3.8415	0.0020	
SOFIX-GSVI	None *	0.4330	34.642	15.495	0.0000	0.4330	27.801	14.265	0.0002	−51.638
	At most 1 *	0.1303	6.8413	3.8415	0.0089	0.1303	6.8413	3.8415	0.0089	
SP 500-GSVI	None *	0.3492	28.065	15.495	0.0004	0.3492	21.048	14.265	0.0037	−84.287
	At most 1 *	0.1334	7.0175	3.8415	0.0081	0.1334	7.0175	3.8415	0.0081	
STI-GSVI	None *	0.3905	32.723	15.495	0.0001	0.3905	24.757	14.265	0.0008	−56.304
	At most 1 *	0.1473	7.9663	3.8415	0.0048	0.1473	7.9663	3.8415	0.0048	
TADAWUL 30-GSVI	None *	0.3430	34.195	15.495	0.0000	0.3430	20.583	14.265	0.0044	−95.650
	At most 1 *	0.2425	13.612	3.8415	0.0002	0.2425	13.612	3.8415	0.0002	
WIG20-GSVI	None *	0.3394	29.484	15.495	0.0002	0.3394	20.731	14.265	0.0042	−96.813
	At most 1 *	0.1606	8.7536	3.8415	0.0031	0.1606	8.7536	3.8415	0.0031	
XU 100 GSVI	None *	0.3360	30.076	15.495	0.0002	0.3360	20.476	14.265	0.0046	−94.258
	At most 1 *	0.1747	9.5995	3.8415	0.0019	0.1747	9.5995	3.8415	0.0019	

Trace test indicates two cointegrating eqn(s) at the 0.05 level. * Denotes rejection of the hypothesis at the 0.05 level. ** MacKinnon et al. (1999) *p*-values.
Author's calculations using EVIEWS.