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On the Dynamic Changes in the Global Stock Markets' Network during the Russia–Ukraine War

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Abstract: Analysis of the relationships among global stock markets is crucial for international investors, regulators, and policymakers, particularly during a crisis. Complex network theory was applied to analyze the relationship between global stock markets during the Russia–Ukraine war. Daily data from 55 stock markets from 6 August 2021 to 23 September 2023 were retrieved and used to investigate the changes in global stock market networks. The sample period was divided into 22 subsamples, using a 100-day rolling window rolled forward a trading month, and then long-range correlations based on distance matrices were calculated. These distance matrices were utilized to construct stock market networks. Moreover, minimum spanning trees (MSTs) were extracted from these financial networks for analytical purposes. Based on topological and structural analysis, we identified important/central nodes, distinct communities, vulnerable/stable nodes, and changes thereof with the escalation of war. The empirical findings reveal that the Russia–Ukraine war impacted the global stock markets' network. However, its intensity varied with changes in the region and the passage of time due to the level of stock market integration and stage of war escalation, respectively. Stock markets of France, Germany, Canada, and Austria remained the most centrally connected within communities; surprisingly, the USA's stock market is not on this list.

Keywords: Russia–Ukraine war; minimum spanning tree; complex network; time-varying network; global stock markets; topological structure; vulnerable and stable nodes

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1. Introduction

Financial crises have remained pervasive throughout history (Allen et al. 2009). It may occur at any time because of myriad factors. However, in recent years, there has been an alarming increase in the frequency of their occurrence (Adekoya et al. 2022). Due to this increased tendency of crises and their frequent long and short episodes, it has become essential to analyze them more extensively and rigorously. Moreover, it should be studied and investigated emergently because of the lesser response time available and its variant dynamics from preceding crises. The most recent and prominent crisis is the Russia–Ukraine war (geopolitical situation), which has global implications and the potential to trigger global financial crises.

This war began when all the diplomatic attempts to resolve the conflict in Crimea and avert armed confrontation were negated, and Russia proclaimed a "special military operation" against Ukraine on 24 February 2022 (Dole 2022). War may have catastrophic implications worldwide; however, as per Boungou and Yatié (2022), it is premature to approximate the significance of the impacts it may cause. This will depend on various factors like conflict duration and the Russian response to the European sanctions. Further, it will also hinge on the escalation level and corresponding regional and global responses. However, as Adekoya et al. (2022) pointed out, this war may be considered the most notable conflict in Europe after World War II.

The implications of the Russia–Ukraine war may emerge through numerous drains on the world and its economy. For example, historical displacement of people may cause an increase in refugee flow; higher prices for commodities, such as foodstuff and energy, may cause rising inflation levels; reduced business confidence and increased uncertainty for investors may further affect prices of items; stringent financial conditions possibly lead to capital flight from emerging markets, and neighboring economies in specific may face interruption in trade, supply chains, and remittances (Kammer et al. 2022; Orhan 2022). Obviously, the most substantial consequence of the Russian–Ukraine conflict is the loss of lives and humanitarian crises related to a large number of people besieged and ousted (Orhan 2022). The war generated one of the fastest mounting refugee pressure after World War II, with more than 4 million displaced persons, about half of whom are children, departing from Ukraine in the first month of the aggression. In addition, 6.5 million people are expected to be expatriated within Ukraine, with about one-third of the population needing emergent humanitarian assistance (Guenette et al. 2022). The contest is expected to affect the world economy and global stock markets.

These expected economic effects of the Russia–Ukraine conflict are detailed below. The Russia–Ukraine war, in addition to a humanitarian disaster, may severely disrupt the global economy, primarily due to the significance of Russia, Ukraine, and their bordering countries. The impairment may occur in food insecurity, energy crises, and supply chains. Firstly, Russia and Ukraine have a significant position in the global economy (Orhan 2022) even though Russia and Ukraine's combined trade constitutes less than 2% of world commerce (Dole 2022). They are still critical international economic actors (Mbah and Wasum 2022); both countries are considered the world's bread baskets. They provide 30% of world wheat and barley, more than 50% of its sunflower oil, and 20% of its maize; Saudi Arabia is the only country that has more oil exports than Russia, and Russia supplies about one-fifth of the world's natural gas and one-ninth of its oil requirements (Orhan 2022). European countries are highly dependent on Russian energy exports to ignite their economy; about 25% of their oil and 40% of their gas needs are fulfilled through this source (Adekoya et al. 2022). Russia and Belarus, one of its neighboring countries, export around a fifth of the world's fertilizer requirements (Orhan 2022). In conclusion, exports of both countries constitute almost 25% of the total global exports (Cohen and Ewing 2022). This economic importance of Russia, Ukraine, and their neighboring countries may cause severe economic consequences owing to evolving war situations.

Secondly, in response to this recent attack, heavy financial sanctions on Russia's Central Bank, ousting their seven core banks from a significant global payment system (Aloisi and Daniel 2022), and holding Russia's gross international reserves kept overseas, impeding Russian capability to settle its financial compulsions (Orhan 2022), were announced by Ukraine's Western allies. In addition to these restrictions, the European leaders imposed additional economic, energy, and transportation sanctions against Russia. Russia is also subject to limitations, including exports, export financing, visa policies, and imports of items with dual uses. In this way, Russia is now considered the most-sanctioned country globally. It is a worldwide popular belief that global financial sanctions enforced against Russia and confiscation of assets/possessions of President Putin's oligarch friends in response to recent Russian aggression against Ukraine will deter Russia from further strikes on Ukraine. Despite this compelling argument, the effects of this catastrophe began to affect the world economy (Mbah and Wasum 2022), and war is still escalating. Albeit having fatal implications for the economy of Russia, it is clear from the reviewed literature that the global economy is now feeling the effects of this calamity (Mbah and Wasum 2022).

Finally, significant world forces were already forecasting this war and considered its beginning only a matter of time (Boungou and Yatié 2022) and prepared themselves for the probable consequences of war. They have now started worrying about escalating prices and shrinking economies. For instance, crude oil prices reached the highest in eight years (Adekoya et al. 2022), leading to higher inflation (Buriyev and Muxiddinova 2022). Commodity prices have risen internationally while the financial market has shrunk substantially (Tank and Ospanova 2022). The fear of rising prices is growing poverty and distracting global commodity production (Orhan 2022). Tug of war in Ukraine may entail a decline in global GDP by 0.5% and 1% by 2022 and 2023, respectively, which is about $1 trillion. Moreover, this war is expected to add up to 3% and about 2% to global inflation in 2022 and 2023, respectively (Tank and Ospanova 2022). These fatal effects will be highly polarized for the European region (Tank and Ospanova 2022) because of Europe's higher dependence on gas and oil imports from Russia, and one-fifth of the total foreign value added also comes from Russia (Kersan-Škabić 2023). Gas and oil's prevailing prices in Europe are now more than ten and two times higher than in the previous year, respectively (Orhan 2022). GDP growth in the Eurozone is predicted to decline by 0.9% and 1.5% in 2202 and 2023, respectively, compared to the February forecast, and an expected rise in inflation to 5.5% and 2.1% in 2022 and 2023, respectively, against forecasts of 3.1%t and 1.3% in 2022 and 2023, respectively, in February (Tank and Ospanova 2022).

All these factors mentioned above emerged gradually and should substantially influence equity markets and their networks, as the global financial markets and economies are interconnected and inseparable (Egan 2022). Hence, the contest also started impacting financial markets. For example, during this war, overall volatility spillover in the commodity universe surged from 35% to 85%, surpassing the level observed during the pandemic (Wang et al. 2022). Financial markets indices showed a drastic decline: S&P 500 decreased by 10%; IMOEX decreased by 33.28%; Wig Poland Index decreased by 10.53%; DAX decreased by 3.96%; FTSE Italia decreased by 4.04% (Boungou and Yatié 2022), and SENSEX decreased by 4.72% (Dole 2022). In conclusion, the humanitarian disaster is becoming an economic crisis that may have global consequences on financial markets and their networks rather than a direct concern of the two nations (Adekoya et al. 2022).

Financial networks originate from network graphs, which are studied widely in mathematics, particularly in graph theory. However, network graphs have numerous applications in health sciences, sociology, statistical physics, economics, and finance, which has given rise to complex network theory. The complex network theory, when applied in finance to study and analyze a financial phenomenon, is termed financial network analysis. Due to their numerous applications, these analyses are gaining increasing importance in finance and becoming an area of immense interest for researchers, academicians, investors, regulators, and policymakers.

A network may be defined as an abstract representation of objects and their relations; in this manner, in a network (G), there is an array of edges (E) and nodes (N) that are linked. Applying complex network theory to global stock markets, one may conceptualize their networks such that each stock market index may be considered a node and their interconnectedness as an edge, which will provide the global stock markets' network. The previous literature on the financial networks of stock markets revealed three things. Firstly, this method of analyzing the relationship of stock markets is more appropriate for studying financial time series because stock market data are often non-parametric, dynamic, and chaotic, exhibiting nonlinear behavior (Han 2019). Secondly, it becomes a more robust tool in times of crisis because it can identify instability and variations in topological features and structural arrangement during such periods (Memon et al. 2019). Thirdly, a handful of the literature on financial networks of stock markets focused on static analysis of these networks; however, little research on temporal global stock markets' networks is available.

Some studies analyzed the impact of the pandemic crisis on stock markets' networks dynamically by using pre- and post-analysis methods. For instance, Aslam et al. (2020) and Zhang et al. (2020) used a temporal network approach to explore the impacts of the crisis on stock markets' networks. In these studies, while analyzing impacts, the researchers mentioned above only focused on two snapshots related to pre- and post-crisis. Whereas market structures and scenarios of crisis development are dynamic, implications related to a crisis on stock markets' network structure should also primarily be dynamic, like a crisis gradually developed into a systemic from a local issue. Hence, a dynamic approach is being proposed in this study to analyze changes in the stock markets' network, considering the all-pervasive nature of this misfortune event and its ubiquitous effects on financial markets. The need for temporal analysis increases significantly during a crisis because less time is available to respond, and its dynamics may vary from preceding crises.

We suggest this dynamic procedure to investigate the formation of the stock markets' network with the Russia–Ukraine war escalation by following Kolaczyk and Csárdi (2014), who proposed such an approach in the network representation of hospital contact data. We believe that stationary analysis of only two networks at a particular point in time, like pre- and post-analysis, to report variations in financial markets' networks due to the Russia–Ukraine war is inadequate. Since it is incapable of identifying variations in networks with the escalation of the Russia–Ukraine war, it is likely that a node with a prominent role in the stock market's network in the pre-crisis period has changed its position several times from the core node to the periphery and/or inversely during the crisis. Then, when it again becomes central in the post-crisis period, it may be overlooked. Moreover, changes in the structural arrangement of nodes and topological features that occurred with the development of the crisis will be missed. Furthermore, stable and vulnerable nodes may not be identified; hence, the network evolutionary process in crisis will remain unexplored. Consequently, international investors following active portfolio management strategies, regulators, and policymakers recommending policy changes during the crisis cannot extract useful information from such analysis to support their decisions. This study attempts to fill this gap. By proposing this macro- and meso-level analysis procedure for networks during a crisis, this study may be placed in the existing literature on shrinking financial networks and tries to extend the current knowledge domain by enriching prevailing pre- and post-crisis methodology in network analysis.

This study may uniquely contribute in the following ways: it will enhance understanding of the topological structure of financial networks of stock markets. This study further aims to understand and analyze the evolutionary process of stock market networks, structural arrangements changes, topological properties, and internal dynamics during war crises. This study will enrich existing pre- and post-crisis analysis methods in financial networks and increase information available for decision-making. It will enable the identification of network structure stability and fragility at the levels of the node(s) and edge(s). Furthermore, this study will provide an in-depth analysis of stock markets' financial networks during the ongoing Russia–Ukraine war. It will extend an understanding of the direct impact of military operations on stock markets' networks. It will add value as many previous studies are limited to a nation or a particular area; in the available literature, static approaches were adopted instead of dynamic ones, and they were unrelated to the Russia–Ukraine war.

The present study is structured as follows: Section 2, "The Literature Review"; Section 3, "Materials and Methods"; Section 4, "Results and Discussion"; and Section 5, "Conclusions".

2. The Literature Review

The geopolitical risk (GPR), like terrorist moves, disputes between nations, and the likelihood of wars, has economic consequences because of increased uncertainty (Caldara and Iacoviello 2022).

2.1. Geopolitical Risk and Uncertainty

Once again, the GPR level has risen tremendously due to the Russia–Ukraine war, which has imposed significant uncertainty because of vulnerability about potential escalation, political and economic stress spillovers to the global economy, sanctions, and response to those sanctions; all these factors would lead to further policy uncertainty (Guenette et al. 2022). Furthermore, the recent Russian invasion of Ukraine is supposed to change the geopolitical landscape (Tank and Ospanova 2022) and threaten the stability of geopolitical relations (Orhan 2022). Russian aggression against Ukraine in 2022 is seen to have reignited geopolitical rivalry amongst the world's superpowers and expressively escalated GPRs. As the literature suggests, these factors have economic consequences and will impact financial markets and their networks. Investment and trade would suffer as firms seek to hedge against an adverse outcome to avoid risk premia owing to high policy uncertainty.

This uncertainty will also have repercussions on the financial markets. For example, Berkman et al. (2011) reported a significant association between political crises and global stock returns' mean and volatility. The empirical fact that equity market returns and risk profile of securities both strongly influenced negatively when political risk was analyzed with financial market performance is also confirmed by another research (Kapar and Buigut 2020). Other studies explored this relationship; Smales (2017) discovered a strong correlation between GPR and market uncertainty by looking at recent key geopolitical events. Similarly, Lehkonen and Heimonen (2015) found a negative association between political uncertainty and equity return and that political risk affected the currency carry trading profit (Dimic et al. 2016). He et al. (2017) examined the economic costs of non-aggressive diplomatic disagreement between Taiwan and mainland China. They concluded that political stress was correlated with a considerable reduction in equity market returns and further reported a connection between lower present stock returns and expected future tension levels. Diplomatic and economic embargoes on Qatar, according to Kapar and Buigut (2020), had a profound effect on the nation's stock market volatility and further demonstrated that the Qatari boycott had a significant influence on Gulf Cooperation Council countries' stock markets, with repercussions spanning across several industries and nations. Various studies reported a considerable impact of GPR on businesses and financial markets; for example, Caldara and Iacoviello (2022) demonstrated different effects on the environment; Rigobon and Sack (2005) documented bond margins and stock returns, and Choi (2022) investigated for stock markets volatility. Geopolitical concerns such as military buildups, war threats, and terrorism have a more substantial negative impact on equity returns than geopolitical acts, as Salisu et al. (2022) have shown in recent research.

2.2. Impact of Military Conflicts and Territorial Disputes on Equity Markets

However, there is a shortage of studies on the direct effects of military conflicts, incursions, and territorial disputes on equity markets. Niederhoffer (1971) examined how international events (such as conflicts and political unrest) affected stock investments worldwide. A few researchers studied the impact of aggressive and non-aggressive global incidents on financial markets (Gu et al. 2021; Hudson and Urquhart 2015). Some studies discussed the impact of war on regional stock market indices; Fernandez (2007), for instance, looked at the effects of conflicts in the Middle East. Guyot (2011) explored the impacts of geopolitics on Islamic countries' financial market indices. In Jordan, the effects of regional conflicts were examined by Alshwawra (2020). Estrada et al. (2020) explored the impact of the suppositional USA–Iran conflict; Zaremba et al. (2022) documented how GPRs affected developing market indices. They all reported an adverse effect of war on equity market indices. However, research that explored the effects of wartime experiences on stock markets is rare, and conclusions drawn are diverse; for instance, Leigh et al. (2003) documented that equity markets became weaker, whereas gold and energy sectors became stronger during the Iraq war. For the invasion of the same nation, the stated results are conflicted. The 1990 invasion of Kuwait by Iraq had a negative commercial impact, but Operation Desert Storm, led by the US, had a favorable one, according to Schneider and Troeger (2006). Finally, according to Bash and Alsaifi (2019), Jamal Khashoggi's disappearance has had a very unfavorable implication on Saudi equity market returns. It is still unclear how the war would affect stock markets because some researchers have found negative consequences (Hudson and Urquhart 2015), while others reported favorable results (Guidolin and La Ferrara 2010).

Conflicts are generally believed to have a detrimental effect on the financial markets, as Gu et al. (2021) and Hudson and Urquhart (2015) reported. However, the research on the repercussions of the Russia–Ukraine war on financial markets is in the preliminary phase. Some researchers took the initiative to document these consequences. Wang et al. (2022) evaluated return and volatility spillover for the commodity market and reported an increase in overall volatility spillover from 35% to 85%; crude oil had become a net transmitter, and other commodities became the net receivers of return spillovers. Adekoya et al. (2022) documented a strong association between oil and other financial assets during periods of war; however, individual results were heterogeneous in net directional pairwise results; oil was observed as a net spillover transmitter in the period before this war, and oil was a net receiver, the spillover effect being transitory and dying over time. The systemic vulnerability of the global financial system increased due to the Russia–Ukraine war (Qureshi et al. 2022), but the response was not long-lasting (Izzeldin et al. 2023). This systemic risk spillover was due to sanctions on Russia that negatively affected the rest of the world (Qureshi et al. 2022), the fear of reduced exports, and investors' concern about suspending business with Russia (Sun and Zhang 2023) due to sanctions negatively driving the market (Kumari et al. 2023). Mohamad (2022) examined flight to safety phenomena and reported flight from the ruble to other currencies and herd behavior between energy commodities and cryptocurrencies. Investment in oil is also considered a safe haven during this war (Diaconaşu et al. 2023). The Russia–Ukraine war harmed the global returns of the stock market. According to Boungou and Yatié (2022), who used panel data to analyze and document this relationship, the impact was significant at the start of the war, particularly in the first fortnight following the Russian attack on Ukraine, and diminished in later weeks. Izzeldin et al. (2023) reached the same conclusion regarding the stock market response to this war. Boubaker et al. (2022) reported varying degrees of negative CARs for global equity market indices due to the Russian invasion of Ukraine. European stock markets also showed abnormal negative returns, which continued even after the event period (Ahmed et al. 2023), with heterogeneous magnitude across countries. A more negative reaction was observed for firms with headquarters in EU countries and countries with great trade dependency on Russia (Sun and Zhang 2023; Tajaddini and Gholipour 2023). Furthermore, the effects were most pronounced for nearby countries, in particular those that share a border with Russia and Ukraine, as well as for UN members that asked for an end to Russia's attack on Ukraine (Boungou and Yatié 2022). Yousaf et al. (2022) concluded that European and Asian countries were more significantly and adversely affected than North American, Latin American, Middle Eastern, and African regions (Yousaf et al. 2022; Ahmed et al. 2023). Policymakers in Europe should reduce their reliance on oil and gas supplies from Russia by pursuing alternate energy sources (Ahmed et al. 2023).

2.3. Network Analysis and Financial Networks

Historically, networks have been studied widely in mathematics and, more precisely, in graph theory. However, it has also been applied in health sciences, sociology, statistical physics, economics, and finance. Examples are the World Wide Web (Huberman 2001), the Internet (Faloutsos et al. 1999), financial networks, the food webs (Pimm 1982), bibliometric analysis like university–industry cooperation, green technology innovation, financial performance relationships (Borges et al. 2022; Qing et al. 2022), and many others. Based on growth networks that have a binary classification, the first are growing networks, e.g., Barabási and Albert (1999) (BA model), and the other are shrinking ones, e.g., The Watts and Strogatz (1998) (WS model). In growing networks, the number of nodes and edges between them grow continuously; on the other hand, in shrinking networks, the number of nodes is fixed (almost fixed). However, a shrinking network does not mean a static one; in both classes, networks evolve with the passage of time. In the case of growing, both nodes and links may increase, and in shrinking network cases, the nodes may remain fixed, and the links between these nodes may change, a process termed network rewiring (Xie et al. 2008).

In finance, network analysis has many valuable applications. For instance, Garlaschelli and Loffredo (2004) applied development and topological characteristics (Fagiolo et al. 2009, 2010), firm connection maps (Bernard et al. 2019; Rungi et al. 2017; Vitali et al. 2011) to webs of global commerce. Networks for technology adoptions were used to examine the transfer of innovations among different disciplines from scientific to any other related field (Acemoglu et al. 2016). Other uses include investigating cross-border exposure (Kubelec and Sá 2010) and international banking networks at the macro (Degryse et al. 2010) and micro levels (Minoiu and Reyes 2013).

A separate body of the research literature on financial webs concentrates on measuring and managing risks, and this is thoroughly investigated by different researchers, such as Cossin and Schellhorn (2007), for credit risk at the company level, Mistrulli (2011) for counterparty risk, and Billio et al. (2012) for market risk. The reason behind the phenomenal growth of this utilization of network analysis is its revealing capabilities reported by various researchers; for instance, Allen et al. (2009) captured the domino effect, and Craig and Von Peter (2014) identified structural arrangements and topological features. According to Mistrulli (2011), this approach can also predict which institutions' failure might result in more significant losses. Few researchers extended discussion from organizational to securities level analysis, such as Cetina et al. (2018), to swap exposures (CDC), Hüser et al. (2018) to bail in able securities, and Cai et al. (2018) and Hale (2012) to syndicate loan. For such research studies for network construction purposes, some researchers use fundamental data, while others apply technical data (Billio et al. 2012; Mantegna 1999). In some rare cases, the relationship between financial institutions belonging to different market segments is under consideration; multiple-layer networks are used in such situations for analytical purposes (Bargigli et al. 2015; Hüser et al. 2018; Langfield et al. 2014; Poledna et al. 2015).

In webs related to finance, links are assigned a value based on associations, either statistical relationships (Bargigli et al. 2015) or causal relationships (Wang et al. 2017); this procedure will generate a complete network (Billio et al. 2012). The literature provides a variety of models for filtering information from such a comprehensive network without defined thresholds, for instance, the Minimum Spanning Tree (MST) (Mantegna 1999). MSTs are constructed using a distance matrix; these distances are calculated based on associations, and such filtered network (MST) has nodes (n) and edges ($n - 1$). n represents the number of nodes, MST built in a way that the sum of distance among these links, without cycles, is the minimum. The distance between nodes is dependent on correlation values; as a method for calculating correlation changes, the structure of MST also changes (Wang et al. 2017). Planar Maximally is another type of filtered network (Tumminello et al. 2005); the construction method is the same as of MST, and only the filtration procedure changed because of the limit of number of nodes (n) and $3(n - 2)$ edges, avoiding the cross of links, which returns the same hierarchical tree as MST and with the added information content.

Other financial webs include the risk spillover (Wang et al. 2021), tail risk spillover (Hautsch et al. 2015), extreme risk spillover (Wang et al. 2017), return spillover (Billio et al. 2012), and networks. Correlation between various stock markets worldwide has also been extensively studied using financial networks, as seen in the work of Adjaouté and Danthine (2004) and Yang et al. (2006).

3. Materials and Methods

3.1. Data

The data relating to the daily closing price of 55 countries' leading stock exchange indices were used to examine the impact of the Russia–Ukraine war on these stock markets. The data were retrieved from DataStream for the period starting from 6 August 2021 to 23 September 2023. The sample period consists of 778 days, approximately 533 trading days per stock market index. The list of these 55 leading stock market indices and their countries is provided in Table A1.

The whole sample duration is sliced into subsamples for temporal analysis purposes and to investigate the dynamic impact of the crisis on the international stock markets' network. Details of such subsample periods are provided in Table 1. The sample period related to the Russia–Ukraine war was divided into 22 subsamples by keeping the date of the Russian attack on Ukraine.

Table 1. Discrete periods and corresponding dates.

S No.	Date	Subsample Period
a	23 December 2021	From 6 August 2021 to 23 December 2021
b	23 January 2022	From 1 September 2021 to 23 January 2022
c	23 February 2022	From 1 October 2021 to 23 February 2022
d	23 March 2022	From 29 October 2021 to 23 March 2022
e	23 April 2022	From 26 November 2021 to 23 April 2022
f	23 May 2022	From 23 December 2021 to 23 May 2022
g	23 June 2022	From 28 January 2022, to 23 June 2022
h	23 July 2022	From 1 March 2022 to 23 July 2022
i	23 August 2022	From 30 March 2022 to 23 August 2022
j	23 September 2022	From 6 May 2022 to 23 September 2022
k	23 October 2022	From 2 June 2022 to 23 October 2022
l	23 November 2022	From 5 July 2022 to 23 November 2022
m	23 December 2022	From 4 August 2022 to 23 December 2022
n	23 January 2023	From 1 September 2022 to 23 January 2023
o	23 February 2023	From 4 October 2022 to 23 February 2023
p	23 March 2023	From 2 November 2022 to 23 March 2023
q	23 April 2023	From 29 November 2022 to 23 April 2023
r	23 May 2023	From 29 December 2022 to 23 May 2023
s	23 June 2023	From 1 February 2023 to 23 June 2023
t	23 July 2023	From 28 February 2022 to 23 July 2023
u	23 August 2023	From 31 March 2023 to 23 August 2023
v	23 September 2023	From 5 May 2023 to 23 September 2023

Every subsample duration comprises 100 trading days, detached by a month, yielding a total of 22 subsamples duration; i.e., the initial subsample begins on 6 August 2021 and ends on 23 December 2021, after 100 trading days; the second subsample begins on 1 September 2021 and ends on 23 January 2022. It continues until the last subsample duration, which runs from 5 May 2023 to 23 September 2023. On 24 February 2022, Russia began a "special military operation" against Ukraine. Nineteen subsamples were taken after this date, while three were taken before. An MST representing each subsample has been drawn separately.

3.2. Network Analysis

The network construction (MSTs) started by computing conventional log returns by applying the following formula:

$$R_i\ (t) = lnp_i(t) - lnp_i(t-1) \tag{1}$$

where $p_i(t)$ and $p_i(t-1)$ represent i stock market index's closing value at time t and $t-1$, sequentially.

The correlation coefficient was calculated based on a long-range approach proposed by Andrews (1991) to evaluate the interconnectedness between stock markets. According to Výrost et al. (2019), this technique is deemed appropriate during a crisis because it can mitigate perceived excessive co-integration, supposed increased volatility, and expected exposure to minor lag reversion across succeeding time intervals of stock market returns.

Andrews (1991) proposed a heteroskedasticity and autocorrelation consistent variance-co-variance matrix for a specified sample size T as

$$\hat{\Omega}_T = \begin{bmatrix} \hat{w}_{i,i} & \hat{w}_{i,j} \\ \hat{w}_{j,i} & \hat{w}_{j,j} \end{bmatrix} = \sum_{m=-T+1}^{T-1} k\left(\frac{m}{B}\right)\hat{\Gamma}(m) \tag{2}$$

where

$$\hat{\Gamma}(m) = \begin{cases} T^{-1}\sum\limits_{t=m+1}^{T}[Z_t Z_{t-m}], & m \geq 0 \\ T^{-1}\sum\limits_{t=m+1}^{T}[Z_{t+m} Z_t], & m < 0 \end{cases} \tag{3}$$

and where $\hat{\Omega}_T$ represents the variance-co-variance matrix between stock markets at time t = 1, 2, . . ., T, Z_t = [ri,t,rj,t]T; k(.) is the quadratic spectral kernel weighting function, and B is the bandwidth parameter that weighs lagged variances and covariances. The highest weight can be achieved by opting for a bandwidth parameter equivalent to four trading days; we pick this automatic choice in the current study. The quadratic spectral kernel function is defined as

$$k\left(x = \frac{m}{B}\right) = \frac{25}{12\pi^2 x^2}\left(\frac{sin\left({}^{6\pi x}/_{5}\right)}{{}^{6\pi x}/_{5}} - cos\left({}^{6\pi x}/_{5}\right)\right) \tag{4}$$

In the end, long-run correlation $\hat{\rho}_{i,j}$ between i and j stock markets' returns is calculated as

$$\hat{\rho}_{i,j} = \frac{\hat{w}_{i,j}}{\sqrt{\hat{w}_{i,i}\hat{w}_{j,j}}} \tag{5}$$

where $\hat{w}_{i,j}$ the covariance between stock markets i and j, and $\sqrt{\hat{w}_{i,i}\hat{w}_{j,j}}$ is the product of the standard deviation of i and j stock markets. Afterward, the distance matrix was calculated by transforming the correlation coefficients using the following Equation:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})} \tag{6}$$

where ρ_{ij} is the long-range correlation between stock market indexes i and j. This converted correlation coefficient matrices into square distance matrices, which are used further to construct stock markets' networks.

In a directed network graph, nodes are connected in a specific order, demonstrating mono-directional flow, unlike an undirected network graph, which shows bi-directional flows in connections. Furthermore, if edges contain information about the intensity of directional flow, the network is weighted; otherwise, it is unweighted.

Every stock market index represents a node in the stock market's network, and interdependence between them is an edge. Resultantly, a weighted network was constructed, for which weights were calculated using Equation (6) proposed by Mantegna and Stanley (1999), who created such a network based on the coefficient of correlations between equity markets in formerly referred groundbreaking research work. Such networks contain substantial independent information in their structure (Buonocore et al. 2016).

MST is a sub-network with nodes (N) and edges ($N-1$), constructed in such a way that the total weight of edges for connected nodes is at its lowest value without cycle. The Kruskal or Prim algorithm (Kruskal 1956) can be used to attain this goal of a minimum-cost network; we choose the Prim approach. An MST is a filter graph that has been used in this study to extract topological properties, structural arrangements, and valuable insights. In order to properly visualize the data and obtain a deeper understanding, this approach to the construction of MST is frequently used in the literature to analyze equity market interdependence (Han 2019; Mantegna 1999; Memon and Yao 2019; Nguyen et al. 2019). Several financial and economic crises were also analyzed using the same technique (Mahamood et al. 2019; Majapa and Gossel 2016; Memon et al. 2019; Yang et al. 2014).

In accordance with the subsample period detailed in Table 1, different MSTs were created using temporal windows. The technique proposed by Blondel et al. (2008) was then used to identify communities to investigate clustering and homogeneity among nodes. MSCI categorization was used afterward to contrast with community structure.

MSTs can conceal many broader network characteristics (Han 2019); for this reason, structural dynamics of MSTs using topological properties such as closeness centrality, degree centrality, and betweenness centrality were analyzed according to Table 2, and changes in these attributes were documented for each subsample duration separately.

The level of the node's ability to operate as a bridge is gauged by its betweenness centrality. According to (Freeman 1977), the influence of a node grows over the network with an increase in the level of betweenness centrality; it may be expressed mathematically as

$$B_c\ (i) = \sum_{a,b \in V} \frac{\lambda(a,\ b|i)}{\lambda(a,\ b)} \tag{7}$$

where V is a collection of stock market indexes; $\lambda(a, b)$ shows the number of shortest paths, and $\lambda(a, b \mid i)$ denotes the number of shortest paths across stock market i.

The reciprocal of the sum of the shortest possible distance from node i to every other node in the network is termed closeness centrality. This metric indicates a node's importance in relation to other nodes across the network (Freeman 1978); it can be calculated as

$$C(V_i) = \frac{(N-1)}{\sum_{j=1}^{n} d\left(V_i V_j\right)} \tag{8}$$

where $d(V_i V_j)$ denotes the shortest paths between stock markets i and j V_i and V_j, which correspond to the smallest number of stock market transverses while moving i stock market to j in the network; N is the number of stock market indices in the network, and $(N-1)$ is a normalization factor.

Temporal network analysis is a robust analytical tool that can capture the dynamic aspect of the effect of the Russia–Ukraine war's escalation on stock markets' networks. In this temporal network analysis, each MST represents a snapshot of co-movement in integrated equity markets affected by the intensification of the Russia–Ukraine war for a certain subsample period. However, this may be difficult for the reader because identifying the most variable and stable entity across many time stamp MSTs is difficult. To overcome this problem, make analysis more robust, and document changes in topological features, the following solution was proposed by Goenawan et al. (2016). A network rewiring approach is adopted through which multi-state static networks are analyzed and explored with efficiency and effectiveness. The most vulnerable/stable nodes and edges across the whole sample period are highlighted by a minimal spanning tree rewiring analysis.

Such an analysis, in return, also provides a series of networks; by following Salamon et al. (2018), the positions of the nodes were maintained across several graphs to enable synchronization, detection of highly rewired nodes, and other properties with statistically high variance. This method can report changes even if the degree of nodes and cost of the nearby nodes for creating MST remained equal (Couzens et al. 2013). Each node in every network in such analysis acts as a vector, a component representing numerous other components, representative of an edge attribute or weight to calculate the rewiring score (Salamon et al. 2018). Equation (9) was used to calculate the variance of these vectors and determine which nodes and/or edges are the most vulnerable/stable

$$D_n - Score = \frac{\sum_{i=0}^{n} \left[distance\left(v_i\, , centroid\right)\right]^2}{n-1} \tag{9}$$

where $D_n - Score$ is the dynamic neighborhood score; V_i vector denotes each node in every network; *centroid* is vector mean, and n represents the number of networks.

Table 2. List of positive correlations with other countries.

S #	Country	Discrete Period Numbers																					
		a	**b**	**c**	**d**	**e**	**f**	**g**	**h**	**i**	**j**	**k**	**l**	**m**	**n**	**o**	**p**	**q**	**r**	**s**	**t**	**u**	**v**
1	Australia	50	51	51	55	39	53	50	54	54	53	52	53	52	53	49	50	51	51	53	52	46	52
2	Austria	51	51	46	48	35	49	48	51	52	51	53	50	51	53	47	52	54	52	53	53	50	51
3	Belgium	52	49	49	44	39	50	53	51	50	50	53	50	52	52	48	51	53	52	51	53	50	51
4	Canada	48	51	49	46	34	52	49	53	54	53	53	54	51	52	50	51	51	50	50	53	49	53
5	Denmark	48	43	19	48	35	45	49	51	50	48	48	50	52	52	42	47	47	48	48	49	46	41
6	Finland	50	45	49	44	36	48	50	51	52	52	53	52	51	52	47	50	53	52	53	52	49	52
7	France	50	45	32	50	40	49	53	51	52	52	52	53	51	51	48	51	53	51	53	52	47	49
8	Germany	49	50	42	48	37	48	53	51	49	53	52	51	50	50	48	50	52	52	52	51	47	55
9	Hong Kong	48	41	46	49	37	30	45	51	43	46	27	34	49	48	48	42	47	49	51	51	49	51
10	Ireland	50	46	49	47	34	47	54	51	51	53	54	52	52	52	48	50	52	51	51	50	47	53
11	Italy	49	52	50	50	52	49	53	54	52	52	52	51	50	50	46	51	52	51	53	53	50	54
12	Japan	46	47	49	54	52	44	49	51	51	53	54	53	52	53	48	48	50	52	53	51	46	49
13	The Netherlands	47	51	51	51	49	52	50	52	51	49	51	51	48	50	50	49	52	50	53	53	50	51
14	New Zealand	47	41	27	47	41	52	47	52	51	51	55	54	53	53	47	49	50	51	47	53	47	50
15	Norway	50	51	37	48	34	48	50	52	53	51	52	52	52	52	44	46	49	50	53	53	47	48
16	Portugal	50	49	47	52	47	51	51	53	48	49	51	51	52	53	50	50	52	52	53	52	48	50
17	Singapore	49	50	47	53	38	49	54	51	53	51	54	53	52	49	48	46	52	50	52	52	49	52
18	Spain	51	48	49	48	36	50	53	51	49	50	53	52	52	53	50	51	54	52	53	53	47	49
19	Sweden	48	46	47	48	39	50	51	52	50	53	51	48	50	51	47	48	52	53	52	53	49	52
20	Switzerland	48	44	22	49	44	50	51	53	50	49	51	52	51	51	48	50	52	50	51	51	47	49
21	The United Kingdom	48	50	50	53	51	53	51	52	51	48	52	52	52	52	50	54	52	52	53	53	47	48
22	The United States	50	51	52	53	52	51	48	52	52	51	51	51	51	51	49	48	51	52	51	53	49	53
23	Argentina	51	37	45	29	33	48	49	50	49	45	51	50	53	53	47	52	51	54	52	52	28	29
24	Brazil	48	49	43	37	32	45	48	52	53	50	51	52	47	44	17	17	49	50	52	49	48	49
25	Chile	47	46	49	49	46	49	50	51	51	51	54	53	53	52	38	43	42	48	49	51	50	53
26	China	41	40	16	36	30	30	46	52	37	41	45	47	49	52	46	46	49	49	50	49	48	46
27	Colombia	22	34	39	45	28	43	46	51	50	52	51	52	48	51	47	50	51	51	50	51	49	52
28	Czechia	43	46	47	49	35	47	52	51	48	50	49	49	48	50	44	47	51	51	49	53	50	43
29	Greece	49	48	48	45	33	45	51	52	50	50	51	51	52	52	40	47	48	48	50	52	51	47
30	Hungary	29	41	45	41	36	42	27	52	42	48	49	49	47	51	48	47	48	49	50	51	24	47
31	India	50	51	48	50	51	50	51	51	52	52	54	52	51	50	44	46	52	51	52	55	46	48
32	Indonesia	48	40	50	36	41	46	49	51	51	41	51	48	49	49	28	35	32	39	49	50	45	33
33	Malaysia	50	47	48	50	36	43	46	52	54	54	53	54	53	53	49	48	50	51	52	53	49	46
34	Mexico	49	51	51	49	34	49	52	52	52	49	51	51	51	51	48	44	47	50	51	51	48	45
35	Pakistan	38	29	45	45	35	46	26	45	40	41	48	48	47	43	38	43	38	37	10	14	33	38
36	Peru	47	42	48	47	33	48	49	53	53	51	49	46	47	48	46	49	50	48	51	53	49	51
37	Philippines	48	43	51	35	37	39	49	52	52	53	53	54	54	53	47	48	49	50	45	44	44	46
38	Poland	51	51	47	51	51	51	53	52	53	49	51	47	49	50	48	50	52	51	52	52	49	55
39	Russia	48	47	45	53	53	46	47	29	40	42	51	51	55	52	48	44	40	42	43	43	47	41
40	South Africa	44	46	48	48	32	51	49	53	51	53	53	47	49	50	48	50	52	51	53	53	49	52
41	South Korea	46	50	47	47	35	39	49	52	53	52	54	51	50	53	47	45	49	50	51	51	49	50
42	Taiwan	42	47	51	52	42	50	50	52	51	54	54	52	53	50	49	47	47	47	52	52	51	50
43	Thailand	52	48	49	54	51	52	50	52	53	52	53	51	53	51	46	48	48	51	49	51	48	51
44	Turkey	20	35	12	41	37	44	53	52	46	35	52	52	51	47	42	38	33	35	47	45	37	34
45	Croatia	46	47	44	50	40	42	49	53	50	51	53	51	53	53	18	43	48	52	52	52	38	28
46	Kazakhstan	46	28	48	38	42	50	32	51	48	45	53	42	29	37	10	25	47	50	46	49	44	38
47	Kenya	27	21	39	43	25	35	44	45	48	50	53	50	45	45	42	49	50	49	52	51	37	40
48	Mauritius	48	49	38	50	53	39	52	51	28	29	40	17	15	9	21	14	34	20	36	46	13	30
49	Morocco	41	36	44	42	33	41	52	53	49	50	54	49	48	25	9	16	12	13	30	41	44	42
50	Nigeria	37	17	44	19	24	9	18	9	5	22	23	34	46	46	38	45	15	15	40	37	12	42
51	Romania	52	50	49	43	33	46	36	50	51	49	53	52	52	50	45	38	43	48	50	53	49	36
52	Serbia	25	30	38	35	27	25	37	24	35	35	42	28	19	44	19	37	30	23	5	10	32	49
53	Slovenia	50	48	45	52	42	50	52	52	53	51	51	52	50	51	42	41	47	49	51	50	50	49
54	Tunisia	19	38	38	42	33	46	13	7	25	13	19	19	16	16	51	39	43	42	47	47	13	37
55	Vietnam	14	27	22	25	31	35	40	51	52	51	54	47	41	39	25	32	43	46	46	46	17	49

4. Results and Discussion

The summary of the number of positive correlation coefficients between countries is provided in Table 2.

In the first subsample period, the number of positive coefficients of correlation was 2447 out of 3025, constituting 80%, and the remaining 20% were negative. This number of positive correlations remained in the range from 70% to 90% during the analysis period, with the highest being at 2747 and the lowest at 2125. The number of positive correlation coefficients among the stock markets during the crisis, in some cases, reached a level of 100% (Chakrabarti et al. 2021; Zaheer et al. 2023). The reason for a reduced number of positive correlations may be associated with a quick response and diminishing impact after the first fortnight, as reported by Boungou and Yatié (2022). However, specific key events may be related to an increase in the number of positive correlations. For instance, the number of positive correlations in the 11th subsample period was 2747, i.e., 90.81% '+ve' and 9.19% '−ve'. This was when the Russian President ordered the first mobilization since World War II, which also triggered protest and evacuation from the country (more details in https://www.reuters.com/world/europe/russias-partial-mobilisation-will-see-300000-drafted-defence-minister-2022-09-21/ (accessed on 4 January 2024)). The number of positive correlations decreased slightly in the 12th subsample period to 2667, i.e., 88.17% '+ve' and 11.83% '−ve'. After that, it remained higher than 78% with a mixed trend in the rest of the period, with the highest at 2703, i.e., 89.36% '+ve' and 10.64% '−ve' in the 20th subsample period. At this time, the EU adopted the 11th package of sanctions, and Switzerland implemented a new round of sanctions in conformity with the European package (more details in https://www.consilium.europa.eu/en/press/press-releases/2023/06/23/russia-s-war-of-aggression-against-ukraine-eu-adopts-11th-package-of-economic-and-individual-sanctions/ (accessed on 4 January 2024) and in https://www.admin.ch/gov/en/start/documentation/media-releases.msg-id-96175.html (accessed on 4 January 2024), respectively).

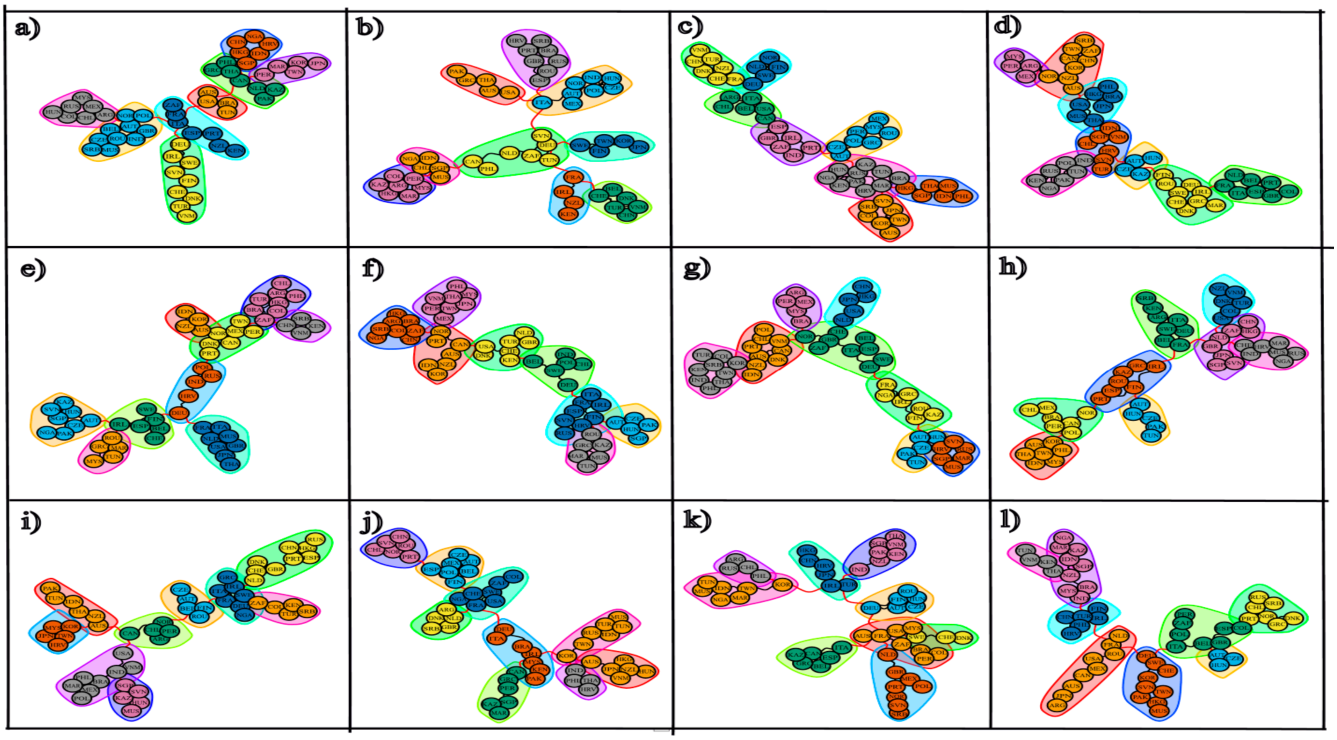
Before the start of the war crisis, the highest number of positive correlations was seen for developed countries' stock markets (1079 out of 1210, i.e., 89.17% '+ve' and 10.83% '−ve') and the lowest for frontier countries' stock markets (391 out of 605, i.e., 64.63% '+ve' and 35.37% '−ve'), which means that developed countries are the most connected and the frontier markets are least connected. This is because of strong economic and political ties among developed countries, with the same tendency of connectivity between stock markets during crises, also reported by Aslam et al. (2020) and (Chakrabarti et al. 2021). The maximum number of positive correlations for any subsample period is 1146 for developed, 1128 for emerging, and 495 for frontier markets. This shows that frontier markets are less linked with other markets. Berger et al. (2011) also identified such low-level interconnectedness of frontier markets with emerging and developed markets, with comparatively better connectivity between developed and emerging stock markets. The possible reason for this better linkage is developed and emerging markets' needs to feed and develop their markets (Zaheer et al. 2023).

Significant coefficients of correlation ($-0.5 > \hat{\rho}_{i,j} > 0.5$) with the escalation of the Russia–Ukraine war remained between a maximum of 1653 '+ve' and 118 '−ve' and a minimum of 693 '+ve' and 0 '−ve'. In the first subsample period, the number of significant positive coefficients of correlation was 755 out of 3025, constituting 25% of the entire sample, whereas negative 10 out of 3025 represented less than 1%. This means that more stock market movements are observed in the same direction than in the opposite direction. This number of significant positive correlations remained in the range of 23% to 55% during the period under analysis. On the other hand, significant negative correlations remained lowest at 0% and did not increase more than 1%. This shows that global stock markets are highly interconnected, and this interconnectedness further increases during a crisis.

An average of 257 directional changes in the coefficient of correlation occurred from the first subsample period to the 22nd, with a maximum of 482 occurring from the fifth to the sixth subsample period when the first five packages of sanctions from the EU were imposed on Russia. More directional changes were observed from emerging and frontier markets than developed markets with respect to their proportion in the sample. This finding conforms with Aslam et al. (2020), who reported most directional changes for frontier markets and least for developed ones. Similarly, (Chakrabarti et al. 2021) found that Eurozone markets remained highly correlated before and during a period of the pandemic. This implies that more changes occurred due to the war crisis for emerging and frontier markets than developed ones. A possible explanation for this is the mimicking behavior adopted by emerging and frontier markets during periods of crisis to mitigate impact.

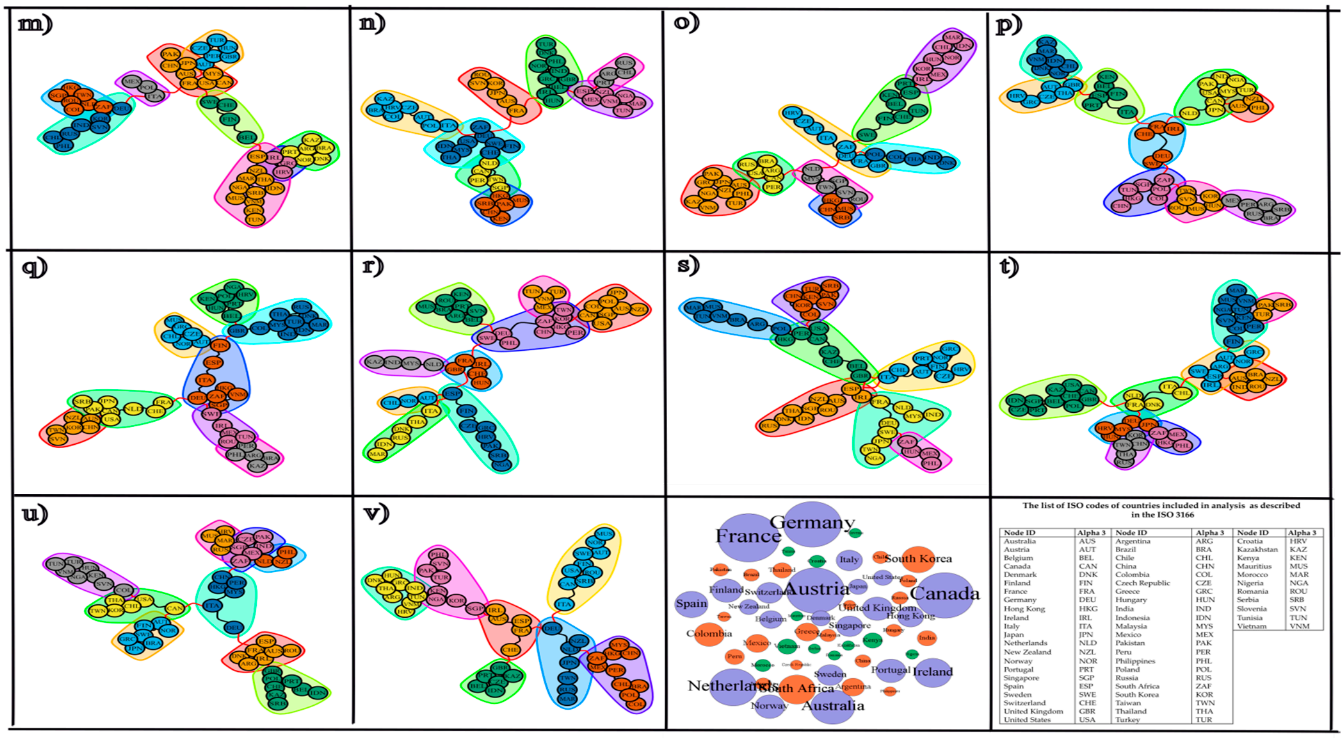
Distance matrices based on long-range correlation were used to construct 22 MSTs for each subsample period by using Equation (6). The communities in each MST of stock markets represent sub-groups of stock markets having more tied connectivity than other parts of MST. In Figure 1a,b, communities are identified using the Louvain algorithm proposed by Blondel et al. (2008) for each subsample period with escalation of war. Different colors were used to show membership for each community for comprehension purposes.

Codes of letters (alpha-3) to refer to a country are used as per ISO 3166-1:2020 (International Organization for Standardization 2020). A list of countries and their alpha-3 codes is provided in the 12th window of Figure 1b. The Morgan Stanley Capital International (MSCI) classification categorizes countries' equity market indices based on economic progress, market accessibility, economy size, and liquidity requirements (classification details are available at https://www.msci.com/market-classification (accessed on 4 January 2024)). These variables make a significant contribution to changes in the community structures (Aslam et al. 2020; Zaheer et al. 2023).



(**a**)

Figure 1. *Cont.*



Node ID	Alpha 3	Node ID	Alpha 3	Node ID	Alpha 3
Australia	AUS	Argentina	ARG	Croatia	HRV
Austria	AUT	Brazil	BRA	Kazakhstan	KAZ
Belgium	BEL	Chile	CHL	Kenya	KEN
Canada	CAN	China	CHN	Mauritius	MUS
Denmark	DNK	Colombia	COL	Morocco	MAR
Finland	FIN	Czech Republic	CZE	Nigeria	NGA
France	FRA	Greece	GRC	Romania	ROU
Germany	DEU	Hungary	HUN	Serbia	SRB
Hong Kong	HKG	India	IND	Slovenia	SVN
Ireland	IRL	Indonesia	IDN	Tunisia	TUN
Italy	ITA	Malaysia	MYS	Vietnam	VNM
Japan	JPN	Mexico	MEX		
Netherlands	NLD	Pakistan	PAK		
New Zealand	NZL	Peru	PER		
Norway	NOR	Philippines	PHL		
Portugal	PRT	Poland	POL		
Singapore	SGP	Russia	RUS		
Spain	ESP	South Africa	ZAF		
Sweden	SWE	South Korea	KOR		
Switzerland	CHE	Taiwan	TWN		
United Kingdom	GBR	Thailand	THA		
United States	USA	Turkey	TUR		

(**b**)

Figure 1. (**a**) Changes in the MST community structure with the escalation of the Russia–Ukraine war from period I to period XII (**a**–**l**). Each MST represents the network's community structure as the Russia–Ukraine war escalated chronologically, as per Table 1. (**b**) Changes in the MST community structure with the escalation of the Russia–Ukraine War from period XIII to period XXII (**m**–**v**). Each MST represents the network's community structure as the Russia–Ukraine war escalated chronologically, as per Table 1, along with a list of countries and their alpha-3 codes per ISO 3166.

(a) Period I: the network exhibits eight communities. The highest degree nodes within communities are in the United States, Austria, Canada, Germany, Italy, Singapore, Peru, and Argentina;
(b) Period II: the network has nine distinct communities. The highest degree nodes within communities are in the United States, Austria, Switzerland, Germany, Sweden, France, Peru, Spain, and Singapore;
(c) Period III: the network at this stage demonstrates eight communities. The highest degree nodes in communities are in South Korea, Austria, Italy, Switzerland, Germany, Thailand, Portugal, and Russia;
(d) Period IV: in this stage of the crisis network, there are eight communities. The highest degree nodes are in Australia, Austria, France, Germany, Japan, Singapore, Mexico, and Poland;
(e) Period V: the network at this stage consists of nine communities. The highest degree nodes in respective communities are in Australia, Hungary, Finland, Canada, France, Germany, Hong Kong, China, and Greece;
(f) Period VI: the network exhibits eight communities. The maximum degree nodes in each community are in Norway, Austria, Sweden, Switzerland, Finland, South Africa, Mexico, and Greece;
(g) Period VII: configuration of network based on eight communities. The highest degree nodes in communities are in Canada, Austria, Norway, Ireland, the Netherlands, Croatia, Brazil, and Colombia;

(h) Period VIII: at this stage, the network has eight communities. The highest degree nodes in respective communities are in South Korea, Austria, France, Canada, Denmark, Finland, the Netherlands, and Switzerland;
(i) Period IX: the network now consists of nine communities. The highest degree nodes are in Australia, Finland, Norway, the Netherlands, France, South Korea, Singapore, India, and Colombia;
(j) Period X: at this stage, nine communities can be observed in the network. The highest degree nodes are in Japan, Finland, Canada, the Netherlands, France, Ireland, Norway, India, and South Korea;
(k) Period XI: the network demonstrates nine communities at this stage. The highest degree nodes are in France, Germany, Canada, Sweden, Ireland, the United Kingdom, New Zealand, Chile, and Indonesia;
(l) Period XII: the networks have eight communities. The highest number of degree nodes are in France, Austria, Belgium, Portugal, Ireland, Germany, New Zealand, and India;
(m) Period XIII: the configuration of networks based on nine communities. The maximum number of degrees in nodes is in France, Austria, Sweden, Portugal, Germany, the Netherlands, Ireland, Italy, and Spain;
(n) Period XIV: at this stage, the network has eight communities. The highest degree nodes are in Australia, Italy, Ireland, the Netherlands, Germany, Hong Kong, Spain, and Portugal;
(o) Period XV: at this stage, the network has eight communities. The highest degree nodes are in Australia, Germany, Belgium, Canada, Colombia, Hong Kong, Ireland, and the Netherlands;
(p) Period XVI: at this stage, the network has nine communities. The highest degree nodes are in Australia, the United Kingdom, Spain, Canada, Norway, France, South Africa, Argentina, and South Korea;
(q) Period XVII: at this stage, the network has eight communities. The highest degree nodes are in Australia, Austria, Portugal, Canada, Malaysia, Germany, Mexico, and Argentina;
(r) Period XVIII: at this stage, the network has nine communities. The highest degree nodes are in Canada, Austria, Belgium, Denmark, Spain, France, South Africa, the Netherlands, and Vietnam;
(s) Period XIX: at this stage, the network has seven communities. The highest degree nodes are in Austria, Australia, Canada, Germany, Vietnam, South Africa, and Colombia;
(t) Period XX: at this stage, the network has nine communities. The highest degree nodes are in Australia, Spain, the United Kingdom, Germany, France, Colombia, South Africa, South Korea, and Pakistan;
(u) Period XXI: at this stage, the network has nine communities. The highest degree nodes are in France, Austria, the United Kingdom, Canada, Hong Kong, the Netherlands, South Africa, Kenya, and Morocco;
(v) Period XXII: at this stage, the network has seven communities. The highest degree nodes are France, Canada, the United Kingdom, Greece, the Netherlands, South Africa and Kenya.

The synopsis of all 22 windows of Figure 1a,b is provided in the 11th window of Figure 1b to avoid confusion and clearly show the position of the node within the community. The rationale, support, and comparison of the above results are provided in this paragraph. In this summary (Figure 1b (11th window)), the size of the node is proportionate to the number of times a country appeared most connected in a community. The color of the node represents the category according to MSCI stock market classification. The developed markets are represented in purple, the emerging markets in orange, and the frontier markets in green, which shows that most of the time, highly connected nodes are Germany, France, Austria, and Canada. The United States showed lesser connectedness with other countries during the crisis despite its strongest correlation in indices of economic policy uncertainty with most countries (Alkan et al. 2023). The fact that the United States did not remain a leading node before and during the crisis was also observed by Aslam et al. (2020). Most of the highly connected countries belong to Europe; as predicted at the start of this war, its fatal effects would be highly polarized for the European region (Tank and Ospanova 2022) because of Europe's higher dependence on gas and oil imports from Russia and its one-fifth of total foreign value added also coming from Russia (Kersan-Škabić 2023). This is also consistent with the findings reported by Liadze et al. (2023). Another possible reason for these high linkages could be their political and economic ties (Zaheer et al. 2023).

Table 3 provides a synopsis of variations in MST topological features like mean closeness and betweenness centrality with the escalation of the Russia–Ukraine war. There is a considerable variation in the topological features of the MSTs. During this study, the mean betweenness centrality varied less. It demonstrated a little shift in the center node's prominence during the investigation period. This center node, however, was altered many times over the investigation period. Such changes would be impossible to identify using static network analysis with two comparison points before and during the war crisis. Each topological feature's temporal dynamicity is presented further in the following paragraphs.

Table 3. Change in networks' topological properties with the escalation of the Russia–Ukraine war from 23 December 2021 to 23 September 2023.

Network	Betweenness Centrality	Closeness Centrality
(a)	0.083	0.195
(b)	0.086	0.187
(c)	0.127	0.135
(d)	0.108	0.155
(e)	0.123	0.137
(f)	0.117	0.142
(g)	0.112	0.149
(h)	0.096	0.170
(i)	0.097	0.170
(j)	0.089	0.183
(k)	0.086	0.188
(l)	0.096	0.171
(m)	0.105	0.158
(n)	0.089	0.183
(o)	0.102	0.165
(p)	0.103	0.161
(q)	0.123	0.138
(r)	0.086	0.189
(s)	0.098	0.169
(t)	0.095	0.173
(u)	0.099	0.167
(v)	0.113	0.149

Period-wise, the observed degrees, closeness centrality, and betweenness centrality are provided in Figures 2 and 3, respectively.

Figure 2 contrasts the number of connections between nodes. Over time, the highest degree node was Austria, Germany, Russia, Austria, Canada, Finland, Canada, the Netherlands, France, Austria, Germany, Hong Kong, Germany, Hong Kong, Germany, and Spain. Most of the time, Germany (six times) and France (four times) were the highest degree nodes. The largest degree fluctuation was recorded for France, and the lesser variation in degree was detected for Nigeria with war development. During turbulence, the number of nodes of degree 1 remained at a minimum of 38.18% and a maximum of 50.09% of the entire sample, suggesting star-like clusters. The exact behavior of stock market networks was also identified by Han (2019) during another crisis.

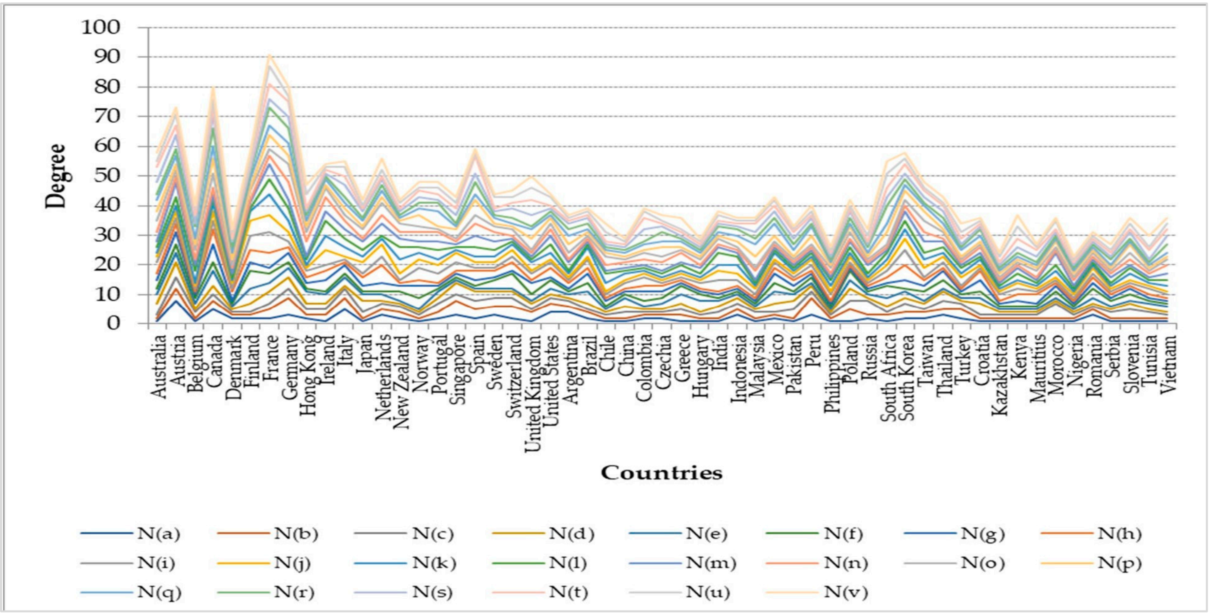


Figure 2. Change in nodes' degrees for each country with the escalation of Russia–Ukraine war from 23 December 2021 to 23 September 2023.

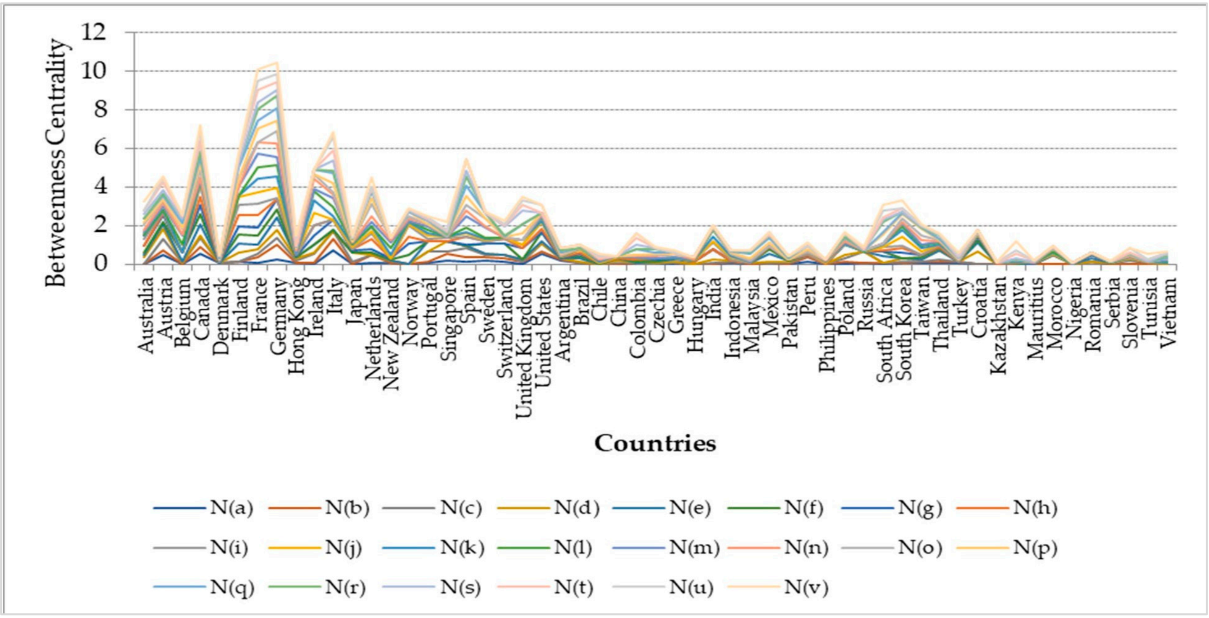


Figure 3. Changes in betweenness centrality for each country with the escalation of the Russia–Ukraine war from 23 December 2021 to 23 September 2023.

Figure 3 depicts the distance between nodes. The greater betweenness centrality of a node shows that it can influence other nodes in the network. The network's center node concerning other nodes shifted from Italy to Germany, Austria, Croatia, Switzerland, the United Kingdom, France, Canada, and Ireland. Most of the time during the Russia–Ukraine war, France (seven times) and Germany (six times) stayed in the center of MST. This means France and Germany ruled virtually all the time in this index and, hence, remained the most influential. This is because Germany and France were affected most by this war. This fact is also concluded by Liadze et al. (2023). The most isolated stock market was Australia, followed by Belgium, Denmark, Canada, Finland, New Zealand, and Ireland. The variance in betweenness centrality is most significant for Ireland and lowest for Nigeria. During the analysis period, the number of zeros for betweenness centrality grew, and betweenness centrality for individual nodes fell; nevertheless, the average betweenness centrality did not change significantly. Han (2019) documented the exact behavior of nodes in the network and argued that it occurred because node clusters were near dominating nodes during the turbulence phase.

Figure 4 depicts the sum of the reciprocal of the smallest route from a node to other nodes, with results indicating the following changes: from Italy to Germany, Austria, Croatia, Switzerland, United Kingdom, France, Norway, and Ireland. Before and during the war crisis, Germany (seven times) and France (six times) remained in the center of MST for most of the time. Changes also occurred in the most distant financial markets, which ranged from Vietnam to Kazakhstan, Serbia, Malaysia, Tunisia, Chile, Russia, China, Morocco, Indonesia, Brazil, Slovenia, and Denmark. Italy displayed the most centrality shifts, while Serbia experienced the least. During the war crisis, the value of closeness centrality grew because nodes moved closer to one another at such times (Han 2019).

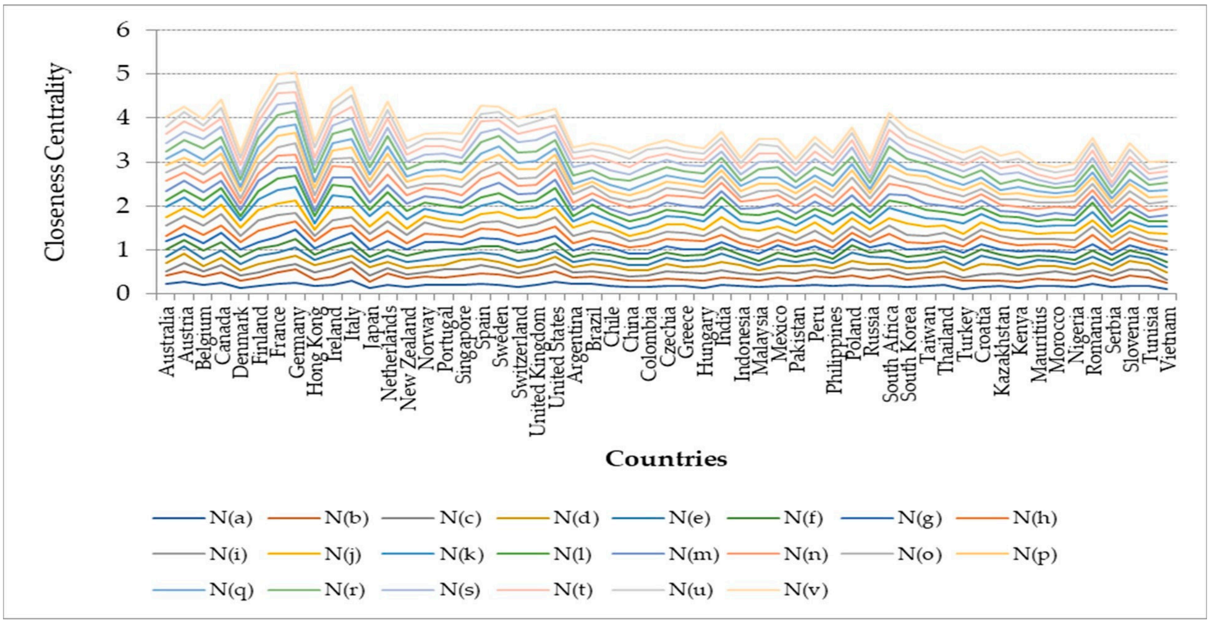


Figure 4. Change in closeness centrality for each country with the escalation of the Russia–Ukraine war from 23 December 2021 to 23 September 2023.

The nodes/edges that were vulnerable changed the most; on the other hand, fewer changes represented the stability of nodes and edges. The most sensitive and stable nodes and linkages during the Russia–Ukraine war escalation were determined using Equation (9). Figure 5 is used as a reference network for MST synchronization purposes.

Figure 6a,b shows changes in the stock markets' network with the escalation of the war, according to the chronology presented in Table 1.

In Figure 6, nodes with the highest variations are shown in red, and nodes with no changes are shown in white. Network linkages due to the minimum cost of the spanning tree are also changed; highly vulnerable linkages are shown in red, and grey is used for stable linkages. Network rewiring occurred due to a change in the minimum cost of connectivity of the network with war development. The topological structure changes are non-trivial and difficult to observe through visualizations. For this purpose, a reference network shown in Figure 5 is used for country nodes' static location, and rewiring between them occurs with the escalation of the war.

Several changes occurred during the war in stock markets and co-movements of markets like Canada, France, Italy, and Austria.

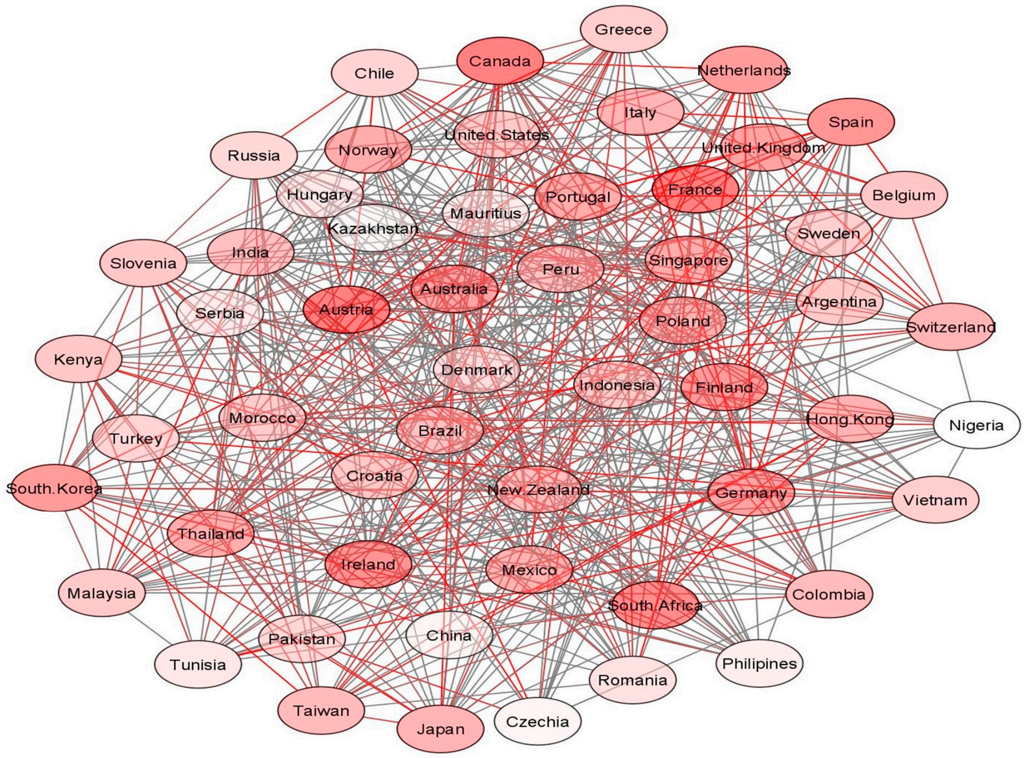
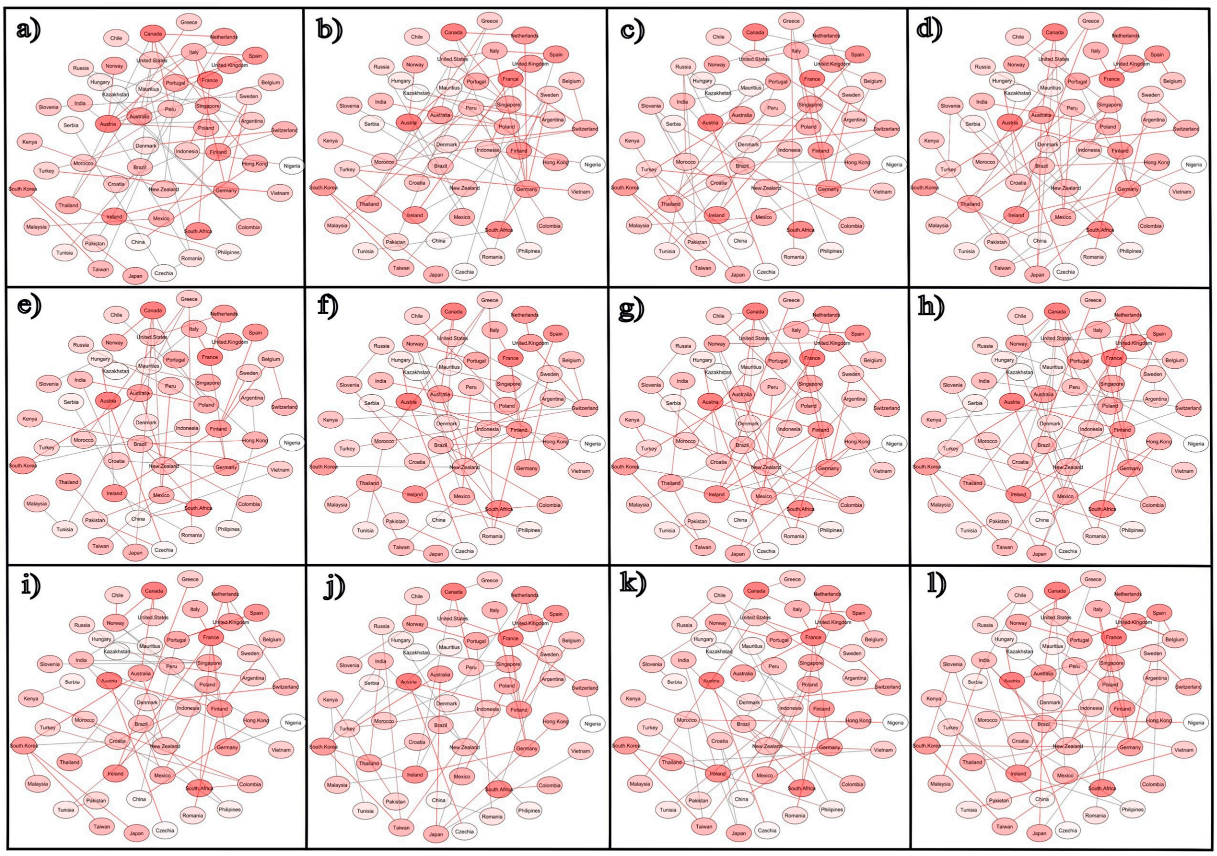
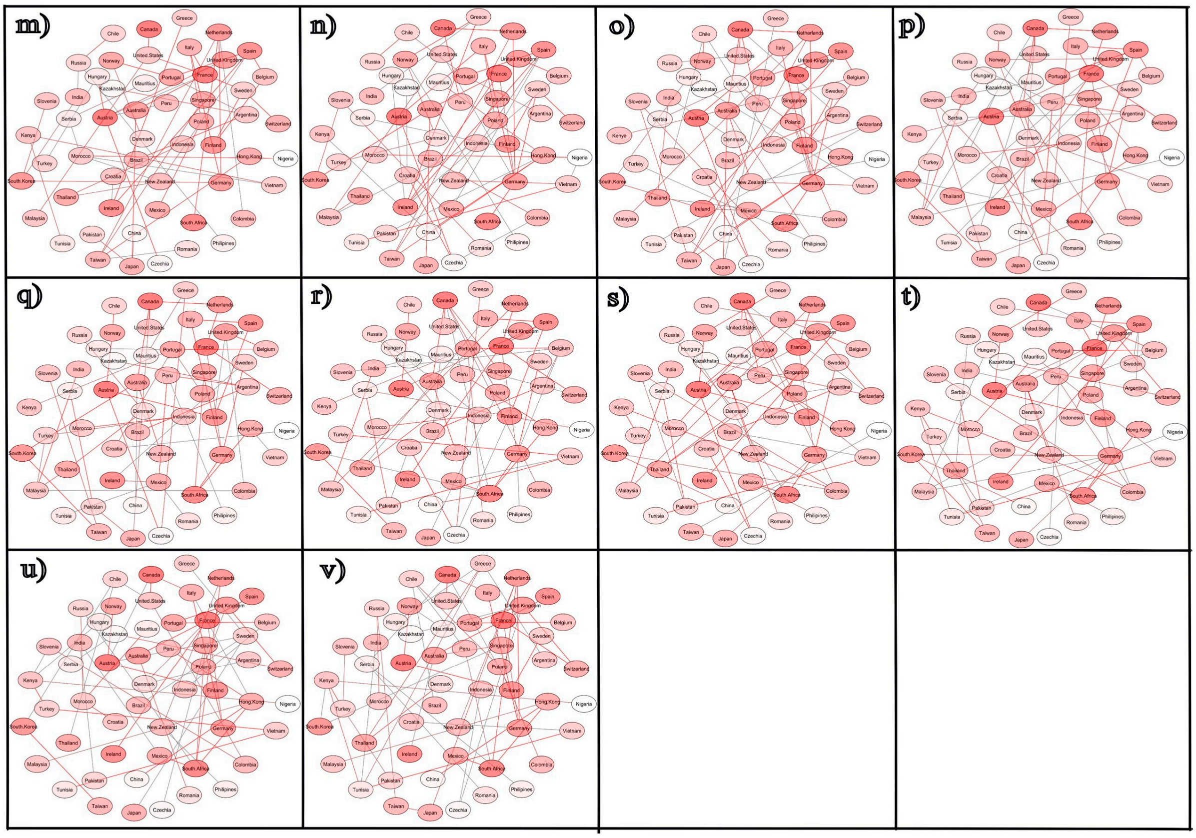


Figure 5. Reference network for observing changes in financial markets' MST network with the escalation of the Russia–Ukraine war from 23 December 2021 to 23 September 2023.



(**a**)

Figure 6. *Cont.*



(**b**)

Figure 6. (**a**) Changes in financial markets' MST network with the escalation of the Russia–Ukraine war from period I to period XII (**a**–**l**). (**b**) Changes in financial markets' MST network with the escalation of the Russia–Ukraine war from period XIII to period XXII (**m**–**v**).

These nodes are identified as the most vulnerable ones compared to China, Kazakhstan, and Czechia; there were few or no changes for Nigeria, which exhibited stable behavior among all nodes. The possible explanation for the stable behavior of this node can be associated with the Nigerian stock market's low level of integration with the rest of the world, despite its anchoring position in West African stock markets, as reported by Emenike (2021). The same conclusion about the linkage between Nigerian and developed stock markets was also documented by Oluseun Olayungbo et al. (2023), who concluded on the availability of diversification and hedging opportunities. The co-movement of other stock markets changed within these two extremes. The vulnerability of nodes from the European region, specifically France and Italy, shows that these countries were affected the most by the war. This fact is also concluded by Liadze et al. (2023). Overall, during uncertain times, the financial networks become vulnerable due to low investor confidence, market instability, disruption of trade and supply chains, sanctions, fear of sanctions and economic disruptions, and investor sentiment and expectations (Aslam and Kang 2015; Aslam et al. 2020; Chakrabarti et al. 2021; Lai et al. 2023; Lai and Hu 2021; Zaheer et al. 2023).

5. Conclusions

In this study, the reaction of the network of global stock markets has been analyzed with the escalation of the Russia–Ukraine war. To attain this objective, 55 indices pertaining to different countries were employed to construct 22 financial networks, which were filtered using the Prim algorithm of an MST. These 22 financial networks were built using a 100-day rolling window rolled forward month's trading days to capture temporal changes. These changes were related to their linking pattern with minimum weight, MST community structure, non-trivial topological properties, and rewiring of MSTs. The changes were analyzed to understand these financial networks and their evolution process. The node/edge level stability and frugality were studied through a network rewiring approach. It is concluded from the results, analysis, and discussion that the Russia–Ukraine war impacted the network of global stock markets. The level of impact varied in intensity with changes in the region and the passage of time due to the level of stock market integration and the Russia–Ukraine war stage of escalation, respectively.

During the Russia–Ukraine war, the global stock markets under analysis remained highly correlated, with those linkages during crises also reported by Chakrabarti et al. (2021). The number of positive correlations ranged between 70% and 90% of the total possible relationships. The Russia–Ukraine war led to increased volatility (Izzeldin et al. 2023), even surpassing the level observed during the pandemic (Wang et al. 2022). The high volatility between the markets could be directly related to strong correlations between those markets (Junior and Franca 2012). The highest number of positive correlations was observed for developed markets and the lowest for frontier markets, which was consistent with the findings of Berger et al. (2011). The number of significant correlations remained between 23% and 55%. Interestingly, the number of significant negative correlations was zero for the 11th, 19th, and 20th subsample periods. The 19th subsample period was when G7 leaders met and decided to "increase the costs to Russia and those supporting its war efforts", and the G7 and EU announced the use of assets that were frozen since the first package of sanctions to rebuild Ukraine (see https://www.whitehouse.gov/briefing-room/statements-releases/2023/05/19/g7-leaders-statement-on-ukraine/ (accessed on 4 January 2024)). This also shows strong integration among global stock markets during the analysis period.

Most directional changes occurred for emerging and frontier markets and less so for developed during periods of crises. This result shows that global stock markets are highly interconnected, and this interconnectedness further increased during the crisis.

The pre- and post-analyses are insufficient to capture the changes during crisis periods, as suggested by Chakrabarti et al. (2021) and Zhang et al. (2020). For this purpose, 22 MSTs were constructed, and changes in the community structure of these financial networks were analyzed. Since it is likely that a node with a prominent role in the network in the pre-crisis period has changed its position several times from core node to periphery and/or inversely in crises and then again became central in the post-crisis period, it may be overlooked. During the analysis period, the number of communities and their membership changed with the escalation of the Russia–Ukraine war. Most of the time, France, Germany, Canada, and Austria remained the most connected nodes within the community. Surprisingly, the United States is not included in this list. This is because of Europe's high dependency on Russia and Ukraine due to its energy and food needs. Liadze et al. (2023) reported more effects of this war on Europe.

The changes in non-trivial topological properties were also analyzed, and the number of nodes with degree 1 increased, showing a star-like structure. The exact behavior of stock market networks was also identified by Han (2019) during another crisis. The number of zeros for betweenness centrality increased, which was documented by Han (2019) as the exact behavior of nodes in the network, suggesting nodes clustering near dominating nodes, and nodes were observed to move closer to each other. France and Germany remained the most influential and central nodes. These two countries may be affected most by the Russia–Ukraine war, which goes against the conclusion drawn by Liadze et al. (2023).

France, Italy, Canada, and Austria were the most vulnerable nodes, whereas Nigeria showed the most stable behavior. The stable behavior of this node may be associated with the Nigerian market's low level of integration with the rest of the world despite its anchoring position in West African stock markets, as reported by Emenike (2021). The same conclusion about the linkage between Nigerian and developed stock markets was also documented by Oluseun Olayungbo et al. (2023), who concluded on the availability of diversification and hedging opportunities. This also refers to more effects of this war on Europe than any other region.

This study will aid different market agents in formulating their strategies. For instance, it will be helpful in the identification of international portfolio diversification opportunities for international institutional and non-institutional investors. It will assist international investors, portfolio managers, regulators, and policymakers in designing portfolio management strategies, optimum intervention courses, and policies to mitigate crisis implications. It may work as a barometer for regulators in deciding the appropriate course of intervention during the trajectory of the crisis period. This will be particularly helpful in designing an early alarming system, and an active intervention option will be available to regulators with such analysis. It will help policymakers to identify stock markets with a dominant or passive role in the future and recommend policy changes accordingly. Furthermore, network rewiring analysis will point out more vulnerable or stable nodes and connections during the crisis. It will be helpful for policymakers in formulating future policies. Hence, the findings of this study will be equally valuable for decision-makers in developing such policies during the crisis that can lessen its effect and decide the future course of action.

An important focus for future research could be the inner dynamics and features that strengthen or weaken the interplay between Russian and European stock markets. Furthermore, a comparison between the economic and network vulnerability during the Russia–Ukraine war may be an interesting area of research.

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Appendix A

Table A1. List of countries and respective stock indices.

S No.	Country	Index Name	S No.	Country	Index Name
1	Australia	S&P/ASX 200	29	Greece	Athens General Composites
2	Austria	ATX	30	Hungary	Budapest SE
3	Belgium	BEL 20	31	India	BSE SENSEX
4	Canada	S&P/TSK	32	Indonesia	IDX Composite
5	Denmark	OMXC 20	33	Malaysia	KLCI
6	Finland	OMX Helsinki 25	34	Mexico	S&P/BMV IPC
7	France	CAC 40	35	Pakistan	KSE-100
8	Germany	DAX	36	Peru	S&P Lima General
9	Hong Kong	FTSE China 50	37	Philippines	PSEi Composite
10	Ireland	ISEQ All Share	38	Poland	WIG20
11	Italy	FTSE MIB	39	Russia	MOEX
12	Japan	Nikkei 225	40	South Africa	South Africa Top 40
13	The Netherlands	AEX	41	South Korea	KOPSI
14	New Zealand	NZX 50	42	Taiwan	Taiwan Weighted
15	Norway	OSE Benchmark	43	Thailand	SET
16	Portugal	PSI 20	44	Turkey	BIST-100
17	Singapore	STI Index	45	Croatia	CROBEX
18	Spain	IBEX 35	46	Kazakhstan	KASE
19	Sweden	OMXS 30	47	Kenya	Kenya NSE 20
20	Switzerland	SMI	48	Mauritius	Semdex

Table A1. *Cont.*

S No.	Country	Index Name	S No.	Country	Index Name
21	The United Kingdom	FTSE 100	49	Morocco	Moroccan All Share
22	The United States	DOW30	50	Nigeria	NSE 30
23	Argentina	S&P Merval	51	Romania	BET
24	Brazil	Bovespa	52	Serbia	Belex 15
25	Chile	S&P CLX IPSA	53	Slovenia	Blue Chip SBITOP
26	China	Shanghai Composite	54	Tunisia	Tunindex
27	Colombia	COLAP	55	Vietnam	HNX 30
28	Czechia	PX			

Note: The first 22 countries from serial 1–22 are developed countries; the next 22 from serial 23–44 are emerging countries, and the next 11 from serial 45–55 are frontier countries, in accordance with Morgan Stanley Capital International (MSCI) classification.

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