

Dynamic Connectedness and Risk Transmission Among Global Sectoral Indices: Findings from COVID-19 and the Russia-Ukraine War¹

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Abstract

This study explores the dynamic relationships and volatility spillovers among global sectoral indices during the Covid-19 pandemic and the Russia-Ukraine war. It evaluates changes in the connectedness of sectoral indices throughout both crisis periods. The finance, materials, industrials, health care, energy, and consumer staples sectors—represented by the MSCI ACWI indices—are analyzed using the TVP-VAR-SV model. The findings reveal significant increases in cross-sectoral connectedness during both crises. During the pandemic, the health care sector was at the core of the connectedness network, exhibiting strong linkages with other sectors. Conversely, during the war, the energy sector assumed a central role, with intensified interactions particularly between the energy sector and the health care, financial, and industrials sectors. Marked increases in volatility were observed in the health care and financial sectors during the pandemic, and in the energy and materials sectors during the war. In the financial sector, short-term shocks predominated during the war, whereas in the energy and health care sectors, short-term shocks in the early phase gave way to long-term, persistent shocks later on. Over time, a changing impulse-response dynamic emerged: short-term effects dominated the health care and industrials sectors during the pandemic, while long-term impacts were more prevalent in the financial and consumer staples sectors. Furthermore, the results underscore the financial sector's leading role in transmitting risk across sectors during both crisis periods. The study's findings also offer important implications for policymakers. The leading role of the financial sector in risk transmission indicates the need to strengthen macro-level policy tools aimed at protecting financial stability.

Keywords: Covid-19, Russia-Ukraine War, MSCI ACWI, TVP-VAR-SV

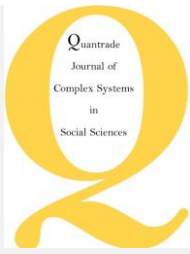
Küresel Sektörel Endeksler Arasındaki Dinamik Bağlantılılık ve Risk Aktarımı: COVID-19 ve Rusya-Ukrayna Savaşından Bulgular

Öz

Bu çalışmada Covid-19 pandemisi ve Rusya-Ukrayna savaşı döneminde küresel sektörel endeksler arasındaki dinamik ilişkiler ve oynaklık etkileşimleri araştırılmıştır. Her iki kriz döneminde sektörel endeksler arasındaki bağlantılılık ilişkisinde değişimler değerlendirilmiştir. MSCI ACWI endeksleri kapsamında yer alan finansal, malzeme, sanayi, sağlık, enerji, temel tüketim malları sektörleri ele alınarak TVP-VAR-SV modeli ile incelenmiştir. Sonuçlar hem pandemi hem de savaş döneminde küresel sektörel endeksler arasındaki bağlantılılıklarda önemli artışlar yaşandığını göstermektedir. Pandemi döneminde sağlık sektörü bağlantılılık yapısının merkezinde yer almış, diğer sektörlerle güçlü bağlantılılık ilişkisi geliştirmiştir. Savaş döneminde ise enerji sektörünün bağlantılılık ilişkisinin merkezinde yer almış; enerji sektörü ile sağlık, finansal ve sanayi sektörleri arasındaki etkileşim güçlenmiştir. Pandemi döneminde sağlık ve finans; savaş

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döneminde ise enerji ve malzeme sektörlerine yüksek volatilité artışları yaşanmıştır. Savaş döneminde finansal sektörde kısa vadeli şoklar baskınken, enerji ve sağlık sektörlerinde savaşın ilk dönemlerinde kısa vadeli şoklar, ilerleyen dönemlerde yerini uzun vadeli kalıcı şoklara bırakmıştır. Zamanla değişen etki tepki analiz sonuçları, pandemi döneminde sağlık ve sanayi sektörlerinde kısa vadeli şokların, finansal ve temel tüketim malları sektörlerinde uzun vadeli etkilerin baskın olduğunu göstermektedir. Ayrıca bulgular, finansal sektörünün her iki kriz döneminde de risk aktarımındaki öncü rolünü vurgulamaktadır. Çalışma bulguları politika yapıcılar için de önemli çıkarımlar sağlamaktadır. Finansal sektörün risk aktarımındaki öncü rolü, finansal istikrarı korumaya yönelik makro düzeyde politika araçlarının güçlendirilmesi gerektiğini göstermektedir.

Anahtar Kelimeler: Covid-19, Rusya Ukrayna Savaşı, MSCI ACWI, TVP-VAR-SV

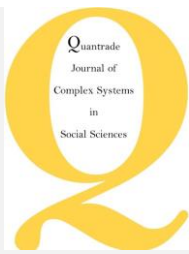
Introduction

The COVID-19 pandemic triggered a crisis arising from both supply- and demand-side disruptions (del Rio-Chanona et al., 2020; Pichler et al., 2021; Baqaee & Farhi, 2022). At the onset of the pandemic, production declined sharply—particularly in China, a central hub in the global supply chain—due to widespread factory shutdowns. This disruption led to supply chain breakdowns and job losses, constituting a direct supply-side shock. In subsequent phases, as production continued to fall, job and income losses became more widespread. Lockdowns and curfews caused severe challenges in sectors such as entertainment, food and beverage, and tourism. Heightened uncertainty led to increased precautionary savings, while prolonged closures caused significant shifts in consumer behaviour. These developments indicate that a demand-side shock occurred in tandem with the supply-side disruption. According to Pichler et al. (2021), the impact of these shocks varied across sectors, underscoring the need to model the economy at a sectoral level and account for inter-sectoral dependencies. As sectors like tourism, transport, food and beverage, entertainment, and automotive nearly ground to a halt (Zeren & Hızarcı, 2020), demand surged in essential goods, health care, and food-related sectors. Meanwhile, the pandemic also profoundly affected financial markets. By late February 2020, financial market risk, volatility, and uncertainty rose dramatically, resulting in substantial stock market losses—approximately 30% within just a few weeks (Fernandez-Perez et al., 2021; Roy & Das, 2022).

The Russia–Ukraine war has largely resulted in a supply-side crisis. Russia is a key global energy provider, accounting for 26% of global natural gas exports, 12% of oil exports, and serving as a major coal exporter (Noorani et al., 2024; Jiang & Chen, 2024). Ukraine, by contrast, holds approximately one-third of the world's most fertile agricultural land and has long been regarded as a breadbasket for both neighbouring and distant regions. Around 80% of Ukraine's arable land is devoted to the cultivation of grains, oilseeds, vegetables, and other annual crops (Countryman et al., 2025). The country is the world's leading exporter of sunflower oil, the fourth-largest exporter of maize and barley, and the fifth-largest exporter of wheat—contributing 40% of the global sunflower oil supply alone. Russia is also the world's largest wheat and barley exporter, accounting for roughly 30% of global exports (Rose, 2023).

The war's impact on the global economy has been both immediate and far-reaching. In response to the invasion, many countries imposed economic sanctions aimed at signalling opposition and exerting financial pressure on Russia. However, a direct consequence of these sanctions has been sharp increases in energy prices. The war has exacerbated global economic challenges, particularly in Europe—which remains heavily dependent on Russian gas—and in an international context still reeling from the aftermath of the COVID-19 pandemic.

Moreover, the effects of the war have extended beyond the energy sector, disrupting broader commodity and financial markets (Aizenman et al., 2024). Russia's blockade of Ukrainian Black Sea ports has prevented the export of vital agricultural products, significantly affecting global food supply chains. This has further intensified the food insecurity initiated during the COVID-19 pandemic, particularly in Sub-Saharan Africa (Obi et al., 2023). Taken together, these developments reveal that the war has had a severe and continuing adverse impact on global markets—especially in the energy, grain, and metal sectors—and that these effects are likely to persist as long as the conflict endures.



Greater integration across markets implies that developments in a few markets can influence others or cause them to move in synchrony, resulting in the transmission of shocks and volatility spillovers (Ekinçi & Gençyürek, 2021). A shock spillover refers to the propagation of an unexpected disturbance from one market to another, whereas volatility spillover occurs when the expected return of one asset is affected by the volatility of another (Duncan & Kabundi, 2013). These concepts, which have gained prominence in recent financial literature, have also been explored within the context of inter-sectoral linkages. Several studies suggest that sectoral diversification may reduce portfolio risk more effectively than cross-market diversification (Cavaglia et al., 2000; Gupta & Basu, 2011). In this context, identifying which sectors act as transmitters or receivers of volatility becomes particularly critical during crisis periods, as such knowledge is essential for achieving effective portfolio diversification.

This study aims to examine the dynamic relationships and volatility spillovers among global sector indices over time. Specifically, it analyses the evolving structure of risk transmission across selected sectors within the MSCI ACWI. The research seeks to uncover the degree of market integration and how it changes during extraordinary periods such as pandemics and geopolitical crises.

This study offers three key contributions to the literature. First, it evaluates the connectedness among sectoral indices within the MSCI framework during both the COVID-19 pandemic and the Russia–Ukraine war. A review of the existing literature reveals a lack of studies assessing the sectoral impact of either crisis, suggesting that this work fills an important gap. Second, it investigates whether there is sectoral heterogeneity in shock propagation during these crises, and whether the financial sector plays a leading role in transmitting shocks. Third, while previous research on sectoral interactions has largely focused on specific countries or regional comparisons, the global dynamics of cross-sector relationships remain underexplored. This study addresses that gap by examining global sectoral interlinkages.

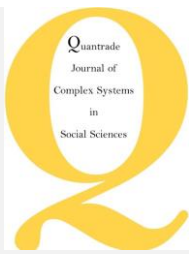
To achieve this, the time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) is employed, as fixed-coefficient models are insufficient for capturing the evolving nature of cross-sector interactions. This approach enables a detailed analysis of volatility spillovers and causality among sectors over time.

1. Literature Review

During the COVID-19 pandemic, a considerable body of research has focused on volatility spillovers between national stock market indices (Mezghani et al., 2021; Cheng et al., 2022; Liu et al., 2022; Rehman et al., 2022; Samitas et al., 2022; Uddin et al., 2022; Ha, 2023; Ghorbel et al., 2024). However, fewer studies have examined the connectedness among sectoral indices. For instance, Khan et al. (2022) analysed the spillover effects of economic policy uncertainty (EPU) on sectoral indices—namely energy, finance, and materials—in Pakistan during the 2008 global financial crisis and the COVID-19 pandemic. Their findings indicate that the finance sector consistently acted as a transmitter of volatility, while the energy sector shifted from being a net recipient during the financial crisis to a transmitter during the pandemic. The materials sector exhibited relatively weak connectedness.

Chirilă (2022), in a study on the Polish stock exchange, found that the banking sector was the most influential in volatility transmission, followed by chemicals, energy, and basic materials. Similarly, Laborda & Olmo (2021) employed network connectivity measures to assess sectoral spillovers in the U.S. during both crises. Their results highlight the prominence of the banking and insurance, energy, technology, and biotechnology sectors as primary shock propagators—with banking and insurance leading during the 2008 crisis and energy taking a central role during the pandemic.

Akhtaruzzaman et al. (2021) explored financial contagion during the pandemic across financial and non-financial firms in China and G7 countries. They concluded that financial firms were more instrumental in spreading contagion. Costa et al. (2022) investigated U.S. sectoral interlinkages before and during the pandemic, finding a substantial rise in total connectedness. Notably, the public utilities and real estate sectors, which had previously been among the least affected, became the most impacted during the pandemic. The



financial sector experienced the largest increase in positive connectedness, underscoring its critical role in international contagion dynamics.

In contrast, Shahzad et al. (2021) reported relatively weak spillovers involving the financial sector in the Chinese stock market, while identifying strong linkages between the energy and utilities sectors. Similarly, Imre (2021) examined the volatility of sectoral indices on the Istanbul Stock Exchange using the EGARCH model. The results revealed that the pandemic increased volatility in the IT, insurance, and food sectors, while reducing it in textile, tourism, and transportation.

Similarly, during the Russia–Ukraine war, a growing body of research has focused on the connectedness among stock market indices (Alam et al., 2022; Almansour et al., 2023; Anyikwa & Phiri, 2023; Frikha et al., 2023; Maurya et al., 2024; Pruchnicka-Grabias & Żebrowska-Suchodolska, 2024; Leone et al., 2025). Choi (2023) examined sectoral return connectivity in the U.S. stock market across various crisis periods. The industrial sector was highly integrated into the return network during the global financial crisis; during the pandemic, the finance, information technology, and industrial sectors became central; and during the Russia–Ukraine war, the industrial, finance, and materials sectors played dominant roles. These variations were attributed to the distinct characteristics of each crisis.

Fitriyah & Mukminatin (2025) analysed sectoral return connectivity in Indonesia during the Russia–Ukraine war. Their results indicate an overall increase in sectoral interdependence during the conflict, with the finance, industrial, infrastructure, and basic materials sectors acting as shock transmitters, while health, transportation, energy, and technology served as shock absorbers. Similarly, Ullah et al. (2023) studied Russian sectoral indices and identified oil and natural gas, finance, metals and mining, public services, and consumer goods and services as shock propagators, whereas the transport, chemical, and telecommunications sectors acted as shock recipients.

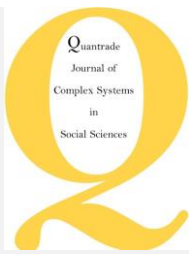
Mahran (2022) investigated volatility linkages among Egypt's sectoral indices during the war and found a rise in sectoral interdependence. In this context, the transport sector emerged as the primary transmitter of volatility.

2. Data and Preliminary Analysis

In this study, the TVP-VAR-SV model is estimated using weekly sector index data for the period 01 November 2018–15 September 2025, covering six global sector indices included in the MSCI ACWI. The analysis is based on logarithmic return series derived from the weekly index data. The MSCI ACWI sector indices are among the most widely used benchmarks for representing global equity market performance, encompassing 23 developed and 24 emerging economies. The sectors analysed in this study are financials, materials, industrials, health care, energy, and consumer staples. Increasing the number of variables in the TVP VAR SV model increases forecasting uncertainty. Therefore, the Consumer Discretionary, Information Technology, Communication Services, Utilities, and Real Estate sectoral indices were excluded from the analysis because they do not directly reflect the supply, demand, and financial transmission channels of crises. An overview and descriptive information of the indices employed in the analysis are presented in Table 1.

Table 1. Definitions of MSCI ACWI sectoral variables

Variable Name	MSCI ACWI Information	Description
Financials	MSCI ACWI Financials Sector Index	Weekly logarithmic returns of global financial sector firms, including banks, insurance companies, and financial services providers.
Materials	MSCI ACWI Materials Sector Index	Weekly log returns of companies involved in mining, metals, chemicals, and raw material production.



Industrials	MSCI ACWI Industrials Sector Index	Log returns of global industrial firms operating in machinery, transportation, defense, construction, and infrastructure.
Health Care	MSCI ACWI Health Care Sector Index	Weekly log returns of firms in pharmaceuticals, biotechnology, medical equipment, and health services.
Energy	MSCI ACWI Energy Sector Index	Weekly logarithmic returns of global oil, natural gas, and energy production and distribution companies.
Consumer Staples	MSCI ACWI Consumer Staples Sector Index	Weekly log returns of firms producing essential goods, including food, beverages, household products, and personal care item.

Table 2 reports the descriptive statistics of weekly logarithmic returns for the selected MSCI sector indices. Among these, the energy sector exhibits the highest volatility, whereas the health care sector displays the lowest. The presence of negative skewness in returns suggests downside risk. All series deviate from normality and exhibit fat tails. Additionally, the results of the Augmented Dickey-Fuller (ADF) test indicate that all return series are stationary at levels. These findings confirm that while the series are stationary, they are not normally distributed. This outcome justifies the application of the TVP-VAR-SV model, which is well-suited to capturing time-varying shocks and volatility dynamics.

Table 2. Descriptive statistics and unit root test results for the weekly logarithmic returns of MSCI ACWI sector indices

Variable	Mean	Std	Skew	Kurt	JB_stat	JB_p	N	ADF_S	ADF_p
Financial	0.11	2.83	-	9.310	683.178	0.0	40	-	0.000
Materials	0.04	3.00	-	13.57	1919.75	0.0	40	-	0.000
Industrials	0.13	2.73	-	10.10	867.870	0.0	40	-	0.000
Health	0.10	2.29	-	6.487	222.024	0.0	40	-	0.000
Energy	0.01	3.80	-	15.04	2544.74	0.0	40	-	0.000
Consumer	0.14	2.92	-	5.418		0.0	40	-	0.000
Staples	0.14	2.92	-	5.418		0.0	40	-	0.000

Note: This table summarizes key statistical properties of the weekly returns for MSCI ACWI sector indices, along with the outcomes of the Jarque-Bera (JB) normality test and the Augmented Dickey-Fuller (ADF) unit root test. The JB test results suggest that the distributions deviate from normality and display fat tails, while the ADF test confirms that all series are level stationary.

Table 3 reports the results of the Ljung-Box and ARCH tests conducted on the weekly logarithmic returns of the sectoral indices. These tests were employed to assess the presence of serial correlation and volatility clustering in the squared returns. While the Ljung-Box test reveals no evidence of serial correlation, the ARCH test results point to significant autoregressive conditional heteroskedasticity. This finding supports the use of volatility-sensitive models such as the TVP-VAR-SV, which can effectively capture time-varying variance structures.

Table 3. Serial correlation and volatility test results for the weekly returns of MSCI ACWI sector indices

Variables	LBQ_ret_st at	LBQ_ret_ p	LBQ_sq_st at	LBQ_sq_ p	ARCH_st at	ARCH_ p
Financial	31.0771	0.1516	290.5117	0.0000	130.6061	0.0000
Materials	25.9035	0.3581	63.6095	0.0000	49.1582	0.0000
Industrial	20.0824	0.6921	277.3280	0.0000	146.7512	0.0000
Health	22.6967	0.5378	187.2183	0.0000	96.9100	0.0000
Energy	33.2455	0.0990	81.1003	0.0000	53.0066	0.0000
Consume	20.6734	0.6579	214.3305	0.0000	116.4363	0.0000

The correlation coefficients among sectoral indices are both positive and statistically significant, indicating a high degree of comovement. The strongest correlation is found between the industrial and financial sectors, whereas the energy sector exhibits the weakest correlation with the others. These findings point to substantial inter-sectoral linkages and underscore the relevance of analysing shock transmission mechanisms across sectors.

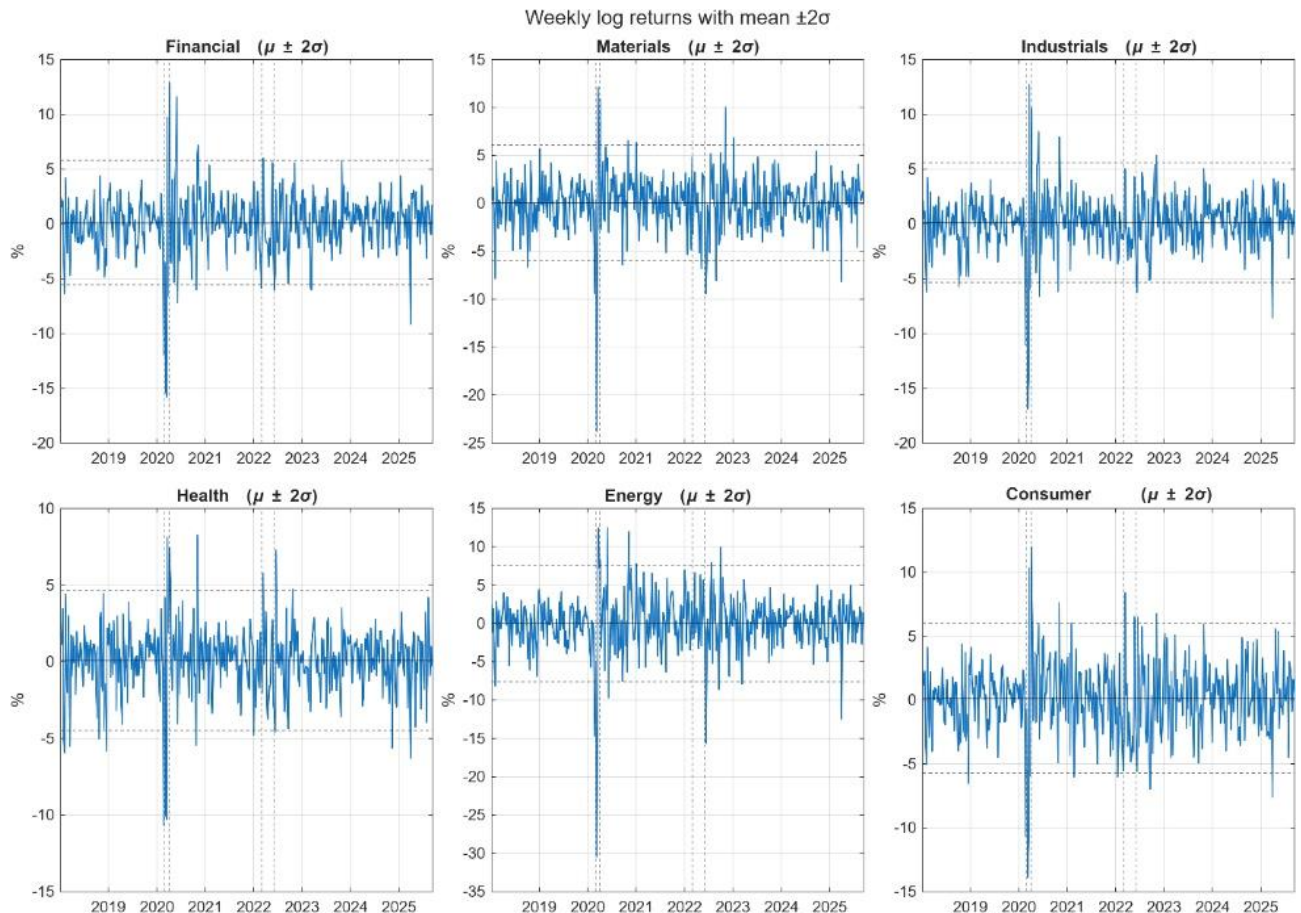
Table 4. Correlation coefficients for weekly returns of the MSCI ACWI sectoral index

Variables	Financial	Materials	Industrials	Health	Energy	Disc
Financial	1					
Materials	0.751***	1				
Industrials	0.919***	0.815***	1			
Health	0.665***	0.594***	0.737***	1		
Energy	0.729***	0.666***	0.691***	0.497***	1	
Consumer	0.794***	0.699***	0.857***	0.679***	0.505***	1

Note: ***, It demonstrates significance at the 1% level.

Figure 1 illustrates the weekly logarithmic returns of selected MSCI sector indices along with their deviations from the respective mean returns. Sharp increases in return volatility are observed during both the COVID-19 pandemic and the Russia–Ukraine war. In both periods, deviations exceeding ± 2 standard deviations (σ) were detected, indicating the presence of extreme market movements. These observations reflect heightened volatility and a synchronized increase in return fluctuations across sectors during major global shocks.

Figure 1. Weekly Log Returns of MSCI ACWI Sector Indices (with average $\pm 2\sigma$ bands)



Preliminary test results reveal that all return series are stationary at levels, deviate from normality, and exhibit volatility clustering. Moreover, the strong cross-sector correlations and the surge in volatility observed during crisis periods indicate that external shocks intensify inter-sectoral dependencies. These findings underscore the importance of employing a modelling approach capable of capturing time-varying structures and stochastic volatility. Accordingly, the TVP-VAR-SV model is adopted in the subsequent stage of the analysis to investigate the dynamics of cross-sectoral shock transmission and volatility spillovers.

3. Methodology

In this study, the interconnectivity among sectoral indices is analysed using the Time-Varying Parameter Vector Autoregressive model with Stochastic Volatility (TVP-VAR-SV), proposed by Nakajima (2011). Several econometric methods have been employed in the literature to examine market interlinkages. One of the earliest is the standard VAR model introduced by Sims (1980), which represents a basic linear regression framework (Qiao et al., 2023). To account for dynamic structural changes, Primiceri (2005) extended the VAR model by incorporating time-varying parameters, resulting in the TVP-VAR model. Building on this, Nakajima (2011) further refined the framework by introducing stochastic volatility into the time-varying structure, arguing that assuming constant volatility may overlook significant variations in shock behavior over time.

Unlike standard fixed-parameter VAR models or GARCH models that focus on univariate volatility, the TVP-VAR-SV model captures both evolving inter-variable relationships and time-varying volatility in a

multivariate context (Zhang et al., 2025). Price shocks can have a time-dependent impact on stock markets. In such a case, fixed-parameter VAR models may be insufficient to capture the dynamic interaction between variables (Toparlı et al., 2019). Furthermore, a fundamental problem with Multivariate GARCH models is that the convergence of optimization algorithms used to estimate parameters is often difficult (Jebabli et al., 2014). For these reasons, the TVP-VAR-SV model developed by Nakajima (2011) was used in the analysis of this study. The methodology of this model is as follows:

$$Ay_t = F_1y_{t-1} + \dots + F_s y_{t-s} + u_t, \quad t = s + q, \dots, n \quad (1)$$

Here, y_t is the $k \times k$ vector of observed variables. A, F_1, \dots, F_s are the coefficient metrics of $k \times k$. The disturbance u_t is a structural shock, and it is assumed that $u_t \sim N(0, \Sigma)$ Here;

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \ddots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_k \end{pmatrix}$$

The simultaneous relationships of the structural shock are determined by iterative definition, assuming that it is sub-triangular.

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21} & \ddots & \ddots & \ddots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \dots & a_{k,k-1} & 1 \end{pmatrix}$$

When the model featured in Equation 1 is rewritten as a reduced VAR model;

$$y_t = B_1 y_{t-1} + \dots + B_s y_{t-s} + A^{-1} \varepsilon_t, \quad \varepsilon_t \sim N(0, I_k) \quad (2)$$

In the formula $B_i = A^{-1} F_i$ is used for $i=1, \dots, s$. The elements in the B_i rows are stacked to form β ($k^2 s \times 1$ vektor) and defined as $X_t = I_k \otimes (y_{t-1}^1, \dots, y_{t-s}^1)$. Here, the \otimes symbol denotes the Kronecker product, and the model is written as follows:

$$y_t = X_t \beta + A^{-1} \Sigma \varepsilon_t \quad (3)$$

According to Equation 3, all parameters do not change over time. By allowing the parameters to change over time in the model, the formula has been rewritten as follows:

$$y_t = X_t \beta_t + A_t^{-1} \Sigma \varepsilon_t, \quad t = s + 1, \dots, n, \quad (4)$$

In the equation, the coefficient β_t and the parameters A_t ve Σ_t vary over time. Finally, if equation 4 is assumed to follow a random walk process as follows;

$$\beta_{t+1} = \beta_t + u_{\beta t}, \quad a_t = a_t + u_{at}, \quad h_{t+1} = h_t + u_{ht},$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N \left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_{\beta} & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right)$$

Here, for $t = s + 1, \dots, n$, $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$ ve $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$ is.

4. Empirical Results

This section presents the empirical results obtained from the TVP-VAR-SV model and the corresponding dynamic connectivity measures generated from the model outputs. The analysis was conducted using weekly logarithmic return data, with the lag order of the VAR component set to $p=2$ based on the Akaike Information Criterion (AIC). Estimation of the TVP-VAR-SV model was carried out using the Markov Chain Monte Carlo (MCMC) simulation method. A total of 120,000 iterations were performed, with the initial 30,000 iterations discarded as burn-in to ensure convergence.

The presentation begins with summary statistics and convergence diagnostics related to the model's estimation parameters. This is followed by an analysis of the time-varying coefficient and volatility dynamics, and finally, the impulse response functions are examined.

The results reported in Table 4 indicate that all Geweke statistics fall below the critical threshold of 1.96 at the 5% significance level, confirming the convergence of the Markov chains. Additionally, Inefficiency Factors (Inef) are below 100 for all parameters, suggesting that the effective sample size is adequate.

Figure 2 further supports these results. As the sample size increases, autocorrelation coefficients tend toward zero, indicating that the MCMC method effectively reduces autocorrelation. The dynamic paths of the chains fluctuate around stable mean values, reflecting a relatively steady sampling process. Moreover, the posterior density plots show that parameter estimates are concentrated within narrow intervals, which confirms convergence to the posterior distribution.

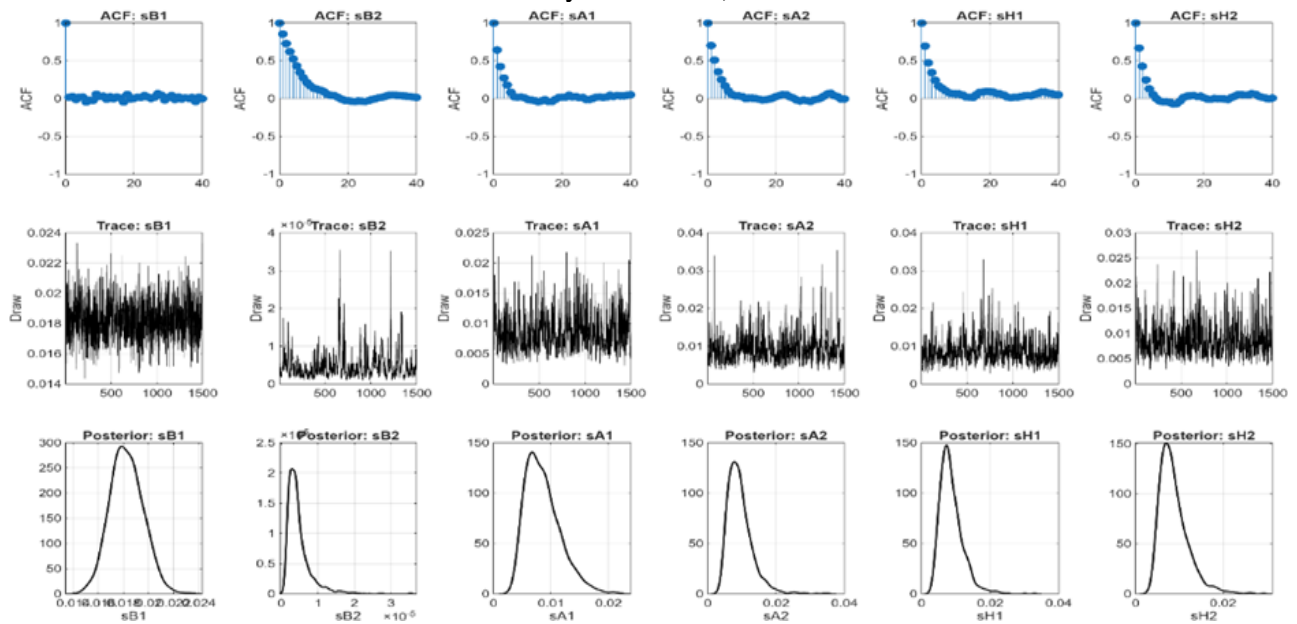
Taken together, the diagnostics presented in Table 4 and Figure 2 provide strong evidence that the MCMC simulation is functioning properly, convergence has been achieved, and the parameter estimates are statistically reliable.

Table 4. TVP-VAR-SV parameter estimation results

Paramet er	Median	St. Dev.	95% Bound	Upper Bound	95% Lower	Gewek e	Inef
sA_1	0.008185	0.003049				0.2152	3.357
6		5	0.015872		0.0043229	1	8
sA_2	0.008787	0.003689	0.018224		0.0046528	0.95434	9
		0.001309				0.7891	1.059
sB_1	0.018176	9	0.020861		0.015823	2	1
	3.8346E-	3.4302E-					5.454
sB_2	06	06	0.000014058		1.4816E-06	1.384	8

sH_1	2	0.008045	4	0.003371	0.017054	0.0040457	1.3079	1	3.811
sH_2	9	0.008060	2	0.003329	0.017463	0.0044696	1.3365	3.283	

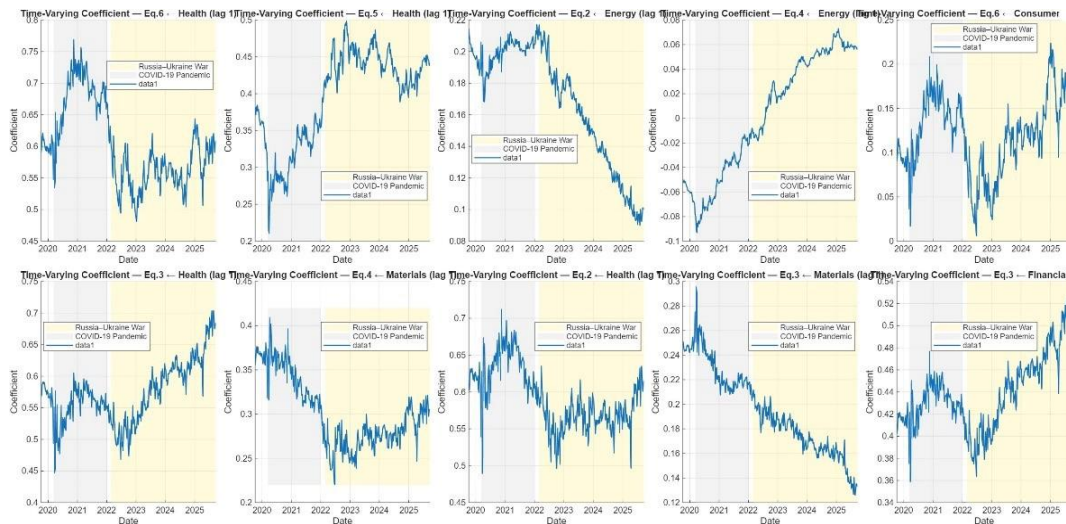
Figure 2. Parameter estimation results graph (autocorrelation coefficients, simulation path and terminal density distribution)



The evolution of inter-sectoral relationships over time was analysed through the dynamic paths of the model coefficients. Unlike time-invariant models, the TVP-VAR-SV framework allows for changing economic relationships by estimating time-varying coefficients. These dynamic paths illustrate how the strength and direction of sectoral linkages evolved during the COVID-19 pandemic and the Russia–Ukraine war. Figure 3 presents the most prominent bilateral interactions based on the estimated dynamic coefficients across all sector pairs. In figure 3, the gray areas show the Covid-19 pandemic shock, and the yellow areas show the Russia-Ukraine war shock.

During the COVID-19 pandemic, a notable increase in interconnectivity was observed among global sectoral indices, indicating widespread volatility spillovers. This observation aligns with the findings of Akhtaruzzaman et al. (2021), Laborda and Olmo (2021), Chirilă (2022) and Costa et al. (2022), who reported significant rises in overall sectoral connectedness during the pandemic period. Among the sectors, the health sector emerged as a central node in the connectedness structure. Given its direct exposure to pandemic-related developments, investor sensitivity to shocks in this sector heightened its linkages with others. In particular, the Consumer Staples sector exhibited strong co-movements with health in the early stages of the pandemic, which can be attributed to shifting consumption patterns driven by public health concerns. Although the initial linkage between the health and energy sectors was weak, it intensified in the later phases of the pandemic. As economic activity resumed, rising energy demand likely contributed to stronger co-movements between the two. Similarly, the connection between the energy and materials sectors also strengthened over time. Supply chain disruptions and rising energy costs in the later stages of the pandemic increased raw material prices, thereby amplifying their connectedness.

Figure 3. Time path graphs of coefficients



Note: The 10 binary relationships with the highest binary correlation coefficients were selected. The MSCI ACWI index ranking in the model is as follows: Financial, Materials, Industrials, Health, Energy, Consumer Staples.

The relationship between the health and industrial sectors followed a non-linear pattern—starting weak, increasing during periods of heightened uncertainty, and tapering off toward the end of the pandemic as industrial production recovered. Likewise, the initially modest linkage between health and materials sectors rose significantly before declining again, suggesting a temporary contagion effect rather than a persistent structural relationship. Finally, the connection between the financial and industrial sectors, which was limited in the early pandemic period, gradually increased. However, with the introduction of vaccines and the easing of lockdowns, this link weakened, likely reflecting stabilizing economic expectations.

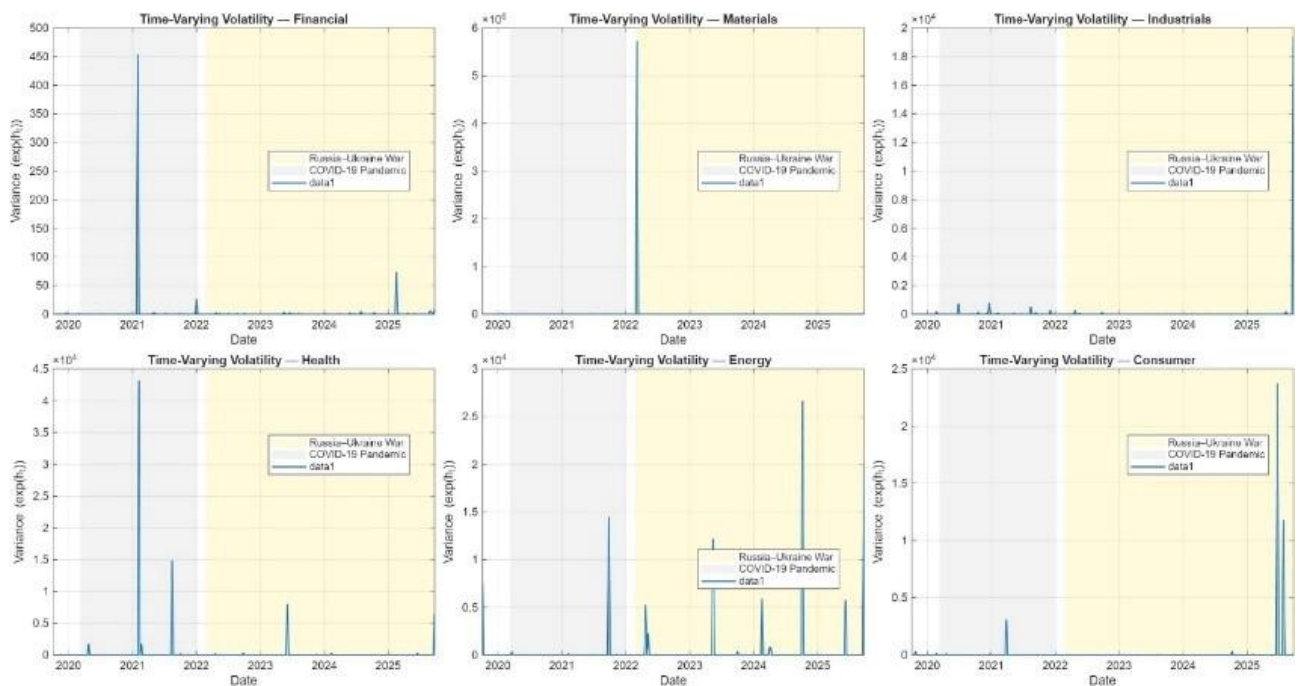
When analysing the correlation structure among sectoral indices during the Russia–Ukraine war, it is observed that, although the overall increase in correlations was not as pronounced as during the COVID-19 pandemic, notable volatility spillovers did occur between specific sectors. This observation is consistent with the findings of Mahran (2022), Ullah et al. (2023), Fitriyah & Mukminatin (2025), who also reported heightened sectoral interconnectivity during the war period. During this time, the link between the health and Consumer Staples sectors remained relatively weak and exhibited fluctuating patterns. In contrast, the connection between the health and energy sectors was both strong and volatile. This can be attributed to the indirect impact of rising energy prices and geopolitical uncertainties on the health sector, amplifying their co-movement. Surprisingly, the previously strong relationship between the energy and materials sectors during the pandemic weakened considerably during the war. This is somewhat counterintuitive, as higher energy costs would typically be expected to elevate production costs in the materials sector, thus strengthening their correlation. One possible explanation is that the heightened uncertainty and increased risk perception led investors to reduce exposure to both sectors, thereby diminishing their connectedness. The relationship between the energy and health sectors, however, continued to intensify throughout the war, while the linkage between the health and industrial sectors also strengthened. This may be driven by increased demand for healthcare services and the structural ties between production chains and medical supply logistics, along with investors' efforts to manage risk by reallocating capital. In the early stages of the war, the correlation between materials and health declined, followed by a slight recovery in later periods. Meanwhile, the materials and industrials sectors, which typically exhibit strong ties due to input-output relationships, experienced a persistent decline in connectedness. This divergence may be explained by shifts in demand, supply chain disruptions, raw material price volatility, and heightened investor risk aversion during crisis periods. Finally,

the financial and industrial sectors became significantly more interconnected as the war progressed, indicating increased exposure of the financial system to industrial activity and broader macroeconomic developments.

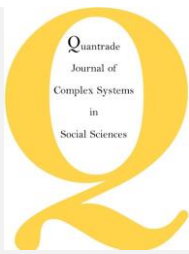
The findings indicate that the relationships among global sectoral indices are dynamic and evolve in response to the nature of the crisis. During the COVID-19 pandemic, a demand-driven integration emerged, with the health sector acting as the central hub of connectedness. In contrast, the Russia–Ukraine war period was characterised by supply-side shocks, with the energy, health, and financial sectors playing dominant roles in bilateral linkages. The time-varying nature of the estimated coefficients suggests that financial integration is not static; rather, it adapts to the underlying characteristics of each crisis. These results underscore the importance of adopting flexible modelling approaches to capture the evolving structure of inter-sectoral relationships under different economic stress scenarios.

To analyse how market uncertainty evolved over time, volatility time path graphs were constructed based on the time-varying stochastic volatility processes in the return variances of each sectoral index.

Figure 4. Volatility time paths



The time-varying volatility charts illustrate how each sector responded to shocks during the COVID-19 pandemic. A surge in volatility was observed across all sectors except for materials. The most pronounced increase occurred in the financial sector, likely due to sudden capital outflows and liquidity shocks triggered by pandemic-related uncertainty. Additional contributing factors may include the announcement of new vaccines, global disparities in vaccine distribution, and geopolitical competition for vaccine access. However, the spike in volatility within the financial sector was short-lived, with no sustained increase in subsequent periods. The health sector, given its central role during the pandemic, also experienced significant volatility. As a key node in the connectedness network, the health sector displayed both high volatility and a rapid response to market shocks, as seen in the volatility and coefficient path charts. In contrast, the industrials sector exhibited relatively moderate volatility increases, though these remained persistent over time—an aspect worth noting. The energy sector also showed elevated volatility, particularly in the second half of 2021. This surge is likely linked to the European energy market crisis during the same period. Meanwhile, the Consumer Staples sector experienced a modest uptick in early 2021, whereas the materials sector showed no significant change in volatility throughout the pandemic period.



During the Russia–Ukraine war, the volatility structure across sectors underwent a significant shift, with the energy sector emerging as the dominant source of volatility. This development can be attributed to heightened uncertainty in energy markets, as geopolitical risks directly impacted energy supply and prices. Another sector that experienced a significant increase in volatility during the war was the materials sector. This sector, which did not show increased volatility during the pandemic, experienced a sharp increase in volatility at the start of the war. This may have stemmed from the negative impact of the war on raw material supply and the supply chain. However, as can be seen in Figure 5, this increase had a short-lived effect and did not continue in the later stages of the war. Volatility in the health sector, which was highly pronounced during the pandemic, also rose during the war, albeit to a lesser extent and primarily over the short term, as reflected in the volatility path. During wartime, increased volatility can be considered particularly high in the financial sector. Although the small and limited lines in the graph might initially lead to misinterpretation, a detailed examination reveals that the variance values in the graph are much higher compared to other graphs (variance values in the financial sector range from 0-500, while in other sectors they range from 0-6). This indicates that the volatility in the financial sector, which may seem small, is actually quite large compared to other sectors. We can also see the increase in volatility in the financial sector in Figure 5. Therefore, uncertainties in financial markets during wartime also fuel increased volatility.

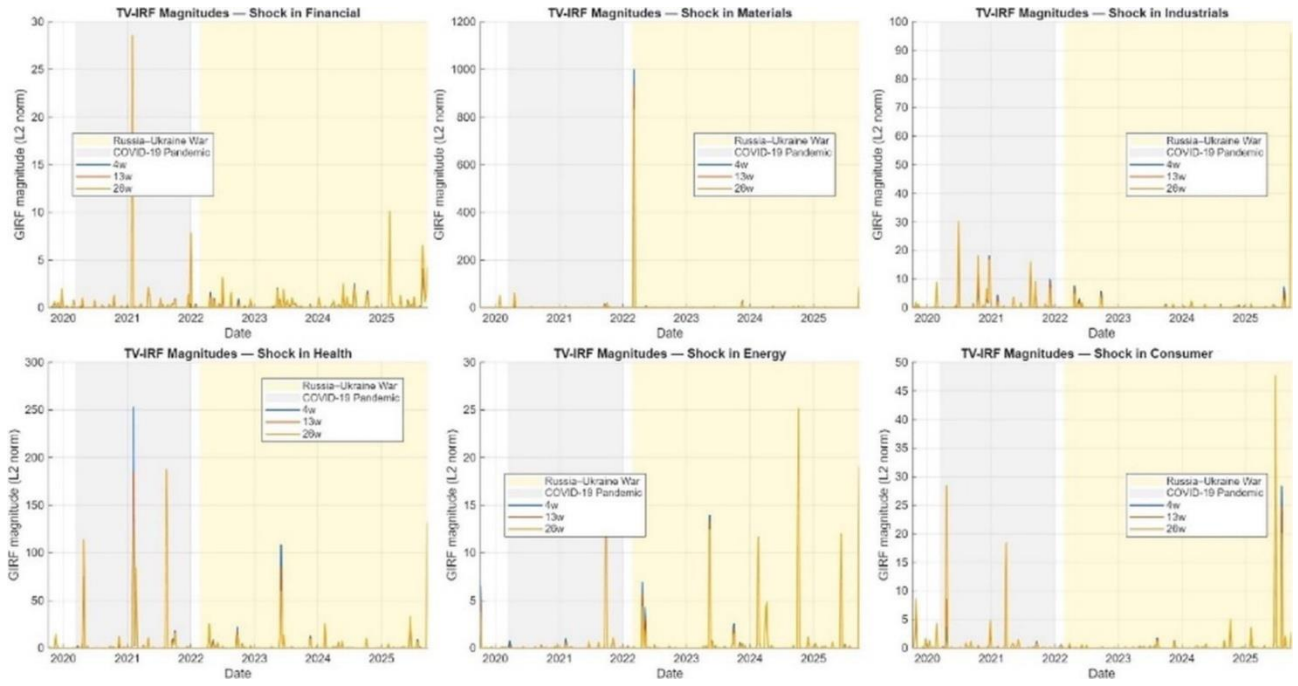
An evaluation of the findings reveals that, during the pandemic, heightened volatility was primarily observed in the health sector, followed by the financial and industrial sectors. In contrast, during the war period, the energy sector experienced the most pronounced volatility, with significant fluctuations also detected in the financial, materials, and health sectors. These results align with the coefficient time path graphs, indicating that the pandemic was driven by both supply and demand shocks, while the war period was predominantly shaped by supply-side disruptions. Accordingly, the volatility dynamics suggest that the mechanisms of risk transmission within the financial system are redefined based on the nature of global shocks. The consistently elevated volatility in the financial sector across both crises underscores its central role in the propagation of systemic risk. This finding is in line with the empirical evidence presented by Akhtaruzzaman et al. (2021), Costa et al. (2022), Chirilă (2022), Khan et al. (2022), Laborda & Olmo (2021), Choi (2023) and Fitriyah & Mukminatn (2025).

Time-varying impact-response graphs (TVIRGs) derived from the TVP-VAR-SV model are presented for horizons of 4, 13, and 26 weeks. Figure 5 shows how TVIRG graphs change over time for different horizons following a shock to the sectoral index.

During the pandemic period, the health sector index—characterised by high vulnerability—was primarily affected by short-term shocks. In contrast, the consumer and financial sector indices experienced more persistent impacts, suggesting that demand-side disturbances exerted sustained pressure on the financial system. In the Russia–Ukraine war period, short-term shock effects were more pronounced in the materials and industrials sectors. However, the energy and health sectors exhibited a different pattern. In particular, the energy sector was initially influenced by short-term shocks, which later evolved into long-term and persistent volatility dynamics as the war progressed.

The results of the impulse response functions reveal that the risk dynamics emerging in financial markets during pandemics and wars exhibit distinct characteristics. During the pandemic, the sectors most affected by shocks—ranked in order—were health, finance, industrials, and consumer staples. This outcome reflects the significant disruptions to both supply and demand caused by lockdowns and production halts. In contrast, during the Russia–Ukraine war, the energy sector was the most severely impacted, followed by the health and finance sectors. These findings underscore the predominance of supply-side shocks during the war period. Given these differences, it is crucial to monitor sector-specific volatility patterns across different types of crises and to design adaptable policy tools aimed at safeguarding financial stability.

Figure 5. Time-varying Impact–Response (TVIRF) graphs obtained from the TVP-VAR-SV model (4, 13 and 26 week horizons)



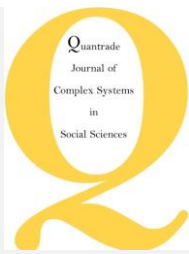
The empirical findings derived from the coefficient time-paths, volatility time-paths, and time-varying impulse response function (TVIRF) graphs presented above provide a detailed depiction of the multiple dimensions of sectoral interactions and shock dynamics during crisis periods. In order to facilitate a more comprehensive and comparative evaluation of these results, the key findings regarding sectoral roles, volatility levels, and the temporal structure of shocks are synthesised and presented in Table 5.

Table 5. Synthesis of Sectoral Roles, Volatility Responses, and Temporal Shock Dynamics Across Crisis Periods

Sector	Pandemic Period: Role & Volatility	Russia–Ukraine War Period: Role & Volatility	Temporal Structure of Shocks
Financials	Moderate connectivity; high volatility	High connectivity; high volatility	Primarily short-term
Health Care	Central sector in connectivity; high volatility	Moderate connectivity; low volatility	Short-term to long-term
Energy	Secondary role in connectivity; low volatility	Low connectivity; very high and persistent volatility	Short-term to long-term
Materials	Limited role; relatively low volatility	Significant short-term volatility increase	Short-term
Industrials	Moderate connectivity; low volatility	Increased connectivity and low volatility	Short-term
Consumer Staples	Low connectivity; low volatility	Low connectivity; low volatility	Long-term

5. Conclusion and Discussion

This study examines how the dynamic relationships and volatility interactions among global sector indices evolved during the COVID-19 pandemic and the Russia–Ukraine war. Specifically, the analysis focuses on



the finance, health, energy, industrials, materials, and consumer staples sectors within the MSCI ACWI framework. To capture time-varying linkages and volatility spillovers during these crisis periods, the Time-Varying Parameter Vector Autoregressive model with Stochastic Volatility (TVP-VAR-SV) was employed.

The results of the analysis indicate that sectoral connectedness increased significantly during both the COVID-19 pandemic and the Russia–Ukraine war. During the pandemic period, the health sector emerged as the central hub of interconnections, with particularly strong linkages identified between the health sector and the consumer staples, energy, industrials, and materials sectors. In contrast, the increase in connectedness during the Russia–Ukraine war was more limited in scale. Nevertheless, substantial linkages were observed between the energy and health sectors, as well as between the health and industrials sectors, and the financial and industrials sectors.

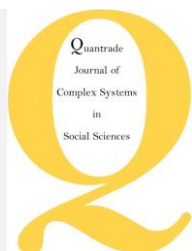
During the pandemic, volatility increased across all sectors except for the materials sector. In this period, the health sector emerged as a key transmitter of shocks, playing a central role in both the network structure and volatility propagation. Although the financial sector recorded the highest spike in volatility, its impact was short-lived and remained contained. In the early stages of the Russia–Ukraine war, the materials sector experienced the sharpest increase in volatility; however, this effect was temporary and did not persist throughout the war. In contrast, the energy sector became increasingly dominant in the volatility structure as the war progressed. These findings underscore that the dynamic relationships among global sector indices are not constant but instead evolve over time, exhibiting distinct patterns depending on the nature of the crisis.

An analysis of the time-varying impulse response functions reveals that, during the pandemic, short-term shocks were more prominent in the health and industrial sectors, whereas the financial and consumer staples sectors exhibited more persistent, long-term responses. In the Russia–Ukraine war period, the financial sector was mainly influenced by short-term shocks. However, in the energy and health sectors, the initial effects of short-term shocks transitioned into long-lasting impacts in the later stages of the conflict. Meanwhile, the surge in volatility observed in the materials sector at the onset of the war generated only a short-term and temporary effect.

According to the time-varying impulse response graphs, short-term shocks played a dominant role in the volatility of the health, industrial, and energy sectors during the pandemic, whereas the financial and consumer staples sectors exhibited more persistent, long-term responses. In the early stages of the Russia–Ukraine war, volatility in the energy sector was initially driven by short-lived shocks, which gradually transitioned into long-term effects as the conflict progressed. The materials sector experienced a temporary spike in volatility at the onset of the war, but its impact dissipated quickly. Short-term shock effects also remained predominant in the financial, health, and industrial sectors throughout the war period.

The findings broadly suggest that during the COVID-19 pandemic, shock dynamics were driven by both demand- and supply-side disruptions centred on the health sector, whereas the Russia–Ukraine war was characterised predominantly by supply-side shocks concentrated in the energy sector. Moreover, crisis-specific differences were observed in the mechanisms of shock propagation—particularly in terms of risk origin, transmission pathways, and persistence. The substantial increases in volatility observed in the financial sector during both crisis periods reaffirm its central role in the transmission of systemic risk. Accordingly, one of the key contributions of this study is the identification of the financial sector as a pivotal actor in shock propagation, regardless of the underlying nature of the crisis.

Finally, the findings yield valuable insights for both portfolio management and policymaking. From an investment perspective, increasing portfolio exposure to the materials and energy sectors—where volatility remained relatively low and shocks were predominantly short-term during the pandemic—and to the industrials and consumer staples sectors during the war, may offer effective risk mitigation strategies. From a policy standpoint, the financial sector’s central role in transmitting systemic risk underscores the need to reinforce macroprudential tools aimed at safeguarding financial stability during periods of heightened uncertainty.



This study has two significant limitations. First, while the study relies solely on sectoral indices within the MSCI AWCI framework, it may not fully reflect regional differences or micro-level sectoral variations in country-specific markets. Second, the study focuses only on two crisis periods (the Covid-19 pandemic and the Russia-Ukraine war). This limits the generalizability of the findings to other crisis and normal periods.

Future research could include geopolitical risk, key uncertainty indicators, energy prices, and macroeconomic variables in the model to more accurately analyze the key determinants of volatility across sectoral indices.

Ethical Considerations of the Study

It is declared that the study was designed to realistically and ethically meet the needs, and that integrity was maintaining in obtaining data, concluding the study, and publishing the results. Ethical committee approval was not required for this research. No research requiring ethics committee approval was conducted in this study.

Informed Consent

There was no need to obtain informed consent from individuals, as the study did not involve any procedure or interventions on human participants.

Author Contributions

Idea/Concept: E.Ş.; Design: E.Ş.; Supervision/Consultancy: E.Ş.; Resources: E.Ş.; Data Collection and/or Processing: E.Ş.; Analysis and/or Interpretation: E.Ş.; Literature Review: E.Ş.; Writing: E.Ş.; Critical Review: E.Ş.

Conflict of Interest Statement

The author declares no conflict of interest.

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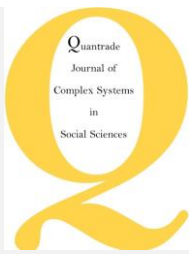
The study did not receive any financial support from individuals or institutions.

Declarations

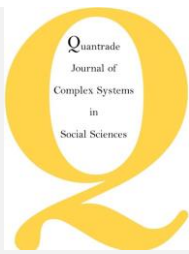
This study has not been presented at any congress.

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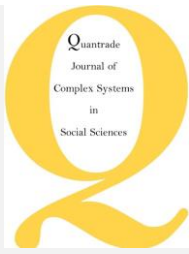
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