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TVP-VAR BASED CARR-VOLATILITY CONNECTEDNESS: EVIDENCE FROM THE RUSSIAN-UKRAINE CONFLICT

TVP-VAR Tabanlı CARR Oynaklık Bağlantılılığı: Rusya-Ukrayna Çatışmasından Kanıtlar

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Keywords:
CARR, Diebold-Yilmaz, TVP-VAR, Volatility Connectedness, Russian-Ukraine War.

JEL Codes:
C11, C22, D53, G17.

Abstract

This paper aims to examine the spillover between volatilities obtained from the Conditional Autoregressive Range (CARR) process with the Time-Varying Parameter Vector Autoregressive (TVP-VAR) based Diebold-Yilmaz approach. We apply Gumbel distributed CARR (1,1) to estimate the volatilities. The summary statistics for the volatility series indicate that the series are not normally distributed, and innovations fit the Gumbel distribution. Also, the obtained volatility series are stationary. We also observe that a significant autocorrelation emerges in all series and the square series. Therefore, using a TVP-VAR model with a time-varying variance-covariance structure is a proper econometric framework to capture all these empirical properties. Moreover, we investigate the impact of the Ukraine-Russia Conflict on global markets as an example. For this purpose, we consider the Russian stock market index and indices selected from among the twenty largest stock exchanges by asset size to perform the connectedness analysis. In TVP-VAR based connectedness approach, we calculate averaged connectedness measures of two panels, without and with the Russian stock exchange. The findings show that the total connectedness index is 79.91% in the first panel, and it increases to 81.44% with the addition of Russian market.

Anahtar Kelimeler:
CARR, Diebold-Yilmaz, TVP-VAR, Oynaklık Bağlantılılığı, Rusya-Ukrayna Savaşı.

JEL Kodları:
C11, C22, D53, G17.

Öz

Bu çalışma Zamanla Değişen Parametreli Vektör Otoregresif (TVP-VAR) tabanlı Diebold-Yılmaz yaklaşımı ile Koşullu Otoregresif Aralık (CARR) sürecinden elde edilen oynaklıklar arasındaki yayılmayı incelemeyi amaçlamaktadır. Çalışmada volatiliteleri tahmin etmek için Gumbel olasılık dağılımına sahip CARR (1,1) uygulanmıştır. Özet istatistikler serilerin normal dağılım göstermediğini ve inovasyonların Gumbel dağılımına uyduğunu göstermektedir. Ayrıca elde edilen oynaklık serileri durağandır. Bunların yanında tüm serilerde ve kare serilerde anlamlı bir otokorelasyonun ortaya çıktığı gözlemlenmiştir. Bu nedenle, zamanla değişen varyans-kovaryans yapısına sahip bir TVP-VAR modeli tüm bu ampirik özellikleri yakalamak için uygun bir ekonometrik çerçevedir. Metodolojik yaklaşıma örnek olarak Ukrayna-Rusya Savaşının küresel piyasalar üzerindeki etkisini ortaya koyan bir uygulama sunulmuştur. Bu amaçla, bağlantılılık analizini gerçekleştirmek için varlık büyüklüğüne göre küresel ölçekte en büyük yirmi borsa arasından seçilen endeksler ile Rus borsa endeksi verisini içeren TVP-VAR analizi iki gruba ayrılmıştır. İlk grubu oluşturan panelde Rus borsa endeksinin oynaklığı dahil edilmezken, ikinci panele dahil edilerek ortalama toplam bağlantılılık endeksleri hesaplanmıştır. Bulgular, toplam bağlantılılık endeksinin ilk panelde %79,91 olduğunu ve Rusya pazarının eklenmesiyle %81,44'e yükseldiğini göstermektedir.

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1. Introduction

In a period of crisis, uncertainties and volatility in the financial markets increase. This situation affects the risk contagion between financial and macroeconomic variables. Standard deviation is used as a statistical indicator to express the risk in market indices, financial asset returns and time-varying macroeconomic indicators, in other words, to identify the changes in these variables. The most widely used model in volatility modelling is the conditional variance model which is the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model by Bollerslev (1986). In GARCH models, the conditional variance in the instant period is not only dependent on the historical values of the error terms, but also on the conditional variances in the past. Therefore, the conditional variance is affected by both past values of residuals and conditional variance values (Ari, 2022). Bollerslev (2010) survey the list of a hundred ARCH-type models including a multivariate form of the model. Multivariate GARCH models are successful approaches to determining volatility spillover between financial asset returns (for additional reading see (Ari, 2020)). On the other hand, unlike these studies, the spillover index method developed by Diebold and Yilmaz (2009) and used to estimate the directional measure of volatility spillover is frequently used. This method is a measure of volatility spillover based on estimation error variance decompositions from vector autoregressions through rolling window estimation; It provides the opportunity to decompose the effect of shocks arising from the presence of j within the estimation error variance of each entity i. Diebold and Yılmaz said that the method in question is both within the domestic markets and between international markets. Although the model published by Diebold and Yilmaz in 2009 was used in many studies, a new model was introduced by the authors, in which the relevant deficiencies were eliminated due to the necessity of ordering the variables and the inability to examine the spread between different types of asset markets (Diebold and Yilmaz, 2009, 2012).

Antonakakis et al. (2020) apply a new Time-Varying parameter Vector Autoregressive (TVP-VAR) approach that overcomes the inadequacies of Diebold and Yilmaz's generalized VAR-based rolling window model. Researchers use the dataset from Antonakakis's (2012) study to compare the original measures of connectedness with their obtained measures. In this approach, the window size does not need to be adjusted if one can use forgetting factors introduced by Koop and Korobilis (2014) and allow variances to vary via Kalman Filter estimation. Thus, sensitivity to deviations and loss of observation are eliminated. As a result, it turns out that the TVP-VAR-based connectedness model adapts instantly to events, while the rolling windows approach either overreacts or softens to the effect of shocks. In addition, the TVP-VAR model can be run to examine dynamic connectedness at lower frequencies and the short period of time series data.

This study examines the spillover between volatilities obtained from the Conditional Autoregressive Range (CARR) process with the TVP-VAR-based Diebold-Yilmaz approach. CARR (Chou, 2005) is an extension of the GARCH models and estimates the volatility of financial assets over their ranges rather than their returns. Unlike Chou (2005), we estimate the conditional distributions of innovations using the Gumbel distribution instead of Exponential or Weibull. We apply the Gumbel CARR model by following the study of Demiralay and Bayraci (2015). For this purpose, we investigate the impact of the Ukraine-Russia War on global markets as an example. This paper also examines the volatility connectedness between the Russian stock market index and indices selected from among the twenty largest stock exchanges by asset size. Studies including the effect of the Russia-Ukraine war on the financial markets can be listed as follows: Boubaker et al. (2022), Boungou and Yatié (2022), Umar et al. (2022), and Yousaf et al. (2022). Boubaker et al. (2022) use an event study methodology and find that this invasion generated negative cumulative abnormal returns for global stock market indices, but with heterogeneous effects. They also indicate that the war had a strong negative impact on the global indices on the event of February 24, 2022, followed by a positive impact on the very next day. Moreover, they conclude while the cumulative effect was generally negative on the global stock markets, the Asian, Middle East and Asia, and pan-American stock markets were an exception to this. Another event study approach, Yousaf et al. (2022), examines the impact of the war on the G20 and other selected stock markets. They find that the European and Asian regions are significantly and adversely affected by the war by the analysis of the abnormal returns on the regional analysis. Boungou and Yatié (2022) apply panel data using a sample of 94 countries to analyze the effect of the Ukraine–Russia war on stock market returns. They indicate two findings: the stock market indices of countries geographically close to the conflict have been the most impacted by the war and the impact was significantly greater for the countries that condemned the invasion than countries that remained neutral (e.g. China, India, and South Africa). Like our example, Umar et al. (2022) examine the return and volatility pass-through between traditional financial assets with a time- and frequency-based TVP-VAR connectedness approach. They consider Russian, European, and US equities (MSCI indices) and bonds (Bloomberg aggregate indices) in their analysis in addition to commodities oil, natural gas, and wheat. The findings of the study are listed as European equities and Russian bonds are the net transmitters of shocks, The war affected the returns and volatility connectedness among them, this effect was in terms of short- and long-term frequencies.

The content of the paper consists of the following parts: After the introduction, which includes the motivation and literature, the second part covers the data set and the method. We present the volatility estimation results after the introduction of the CARR model. Likewise, we give the findings after the third part, where the TVP-VAR connectedness analysis is explained. The fifth part concludes the study.

2. Materials and Method

Chou (2005) applies the CARR model to weekly data sets which are also preferred in other studies where this model is applied. While observation losses occur in the daily frequency data of different markets, weekly frequency data minimizes the observation losses (Demiralay and Bayraci, 2015). For example, the fact that the public holidays are different from country to country and the markets are open on different days, forces us to use weekly data. Therefore, we use the data set that consists of weekly observations of following indices: Dow Jones Industrial Average (USA), Shanghai Composite (CHN), EuroNext 100 (EUR), Nikkei 225 (JPN), Investing.com United Kingdom 100 (GBR), DAX Index (DEU), Nifty 100 (IND), Australian Securities Exchange All Ordinaries (AUS), S&P/TSX Composite Index (CAN), Brazil Index (BRA), Tadawul All Share (SAU), South Africa Top 40 (ZAF), and MOEX Russia (RUS). The data period spans from 7 January 2018 to 15 May 2022.[1]

[1] We considered the stock markets with the highest market capitalization globally and, in their region, when selecting them. Our aim is to create a projection for global developed stock markets. Henceforth, we use country codes instead of indices names. The data can be accessed at https://www.investing.com/indices/world-indices.

We have selected these markets from among the twenty stock exchanges with the largest asset value in the world to obtain an approximation to the global market. By including at least one stock market index from each continent in the data set, we have purposed to represent all different regions of the world.

We aim to examine the volatility spillover between indices to analyse the impact of Russian-Ukraine War. In doing so, we calculate the weekly logarithmic range of the indices to estimate the CARR volatility model of Chou (2005). Figure 1 illustrates the log-range series. There are various variants of CARR models; some researchers have recently extended the CARR models (see among others Ratnayake, 2021). The dynamic specification of the CARR(1,1) model is as follows.

$$\begin{aligned} R_t &= \boldsymbol{\lambda}_t z_t, \quad z_t \sim f(1, \varsigma) \\ \boldsymbol{\lambda}_t &= \omega + \alpha R_{t-1} + \beta \boldsymbol{\lambda}_{t-1} \end{aligned} \tag{1}$$

where R_t is the range and is obtained by $R_t = \max(P_\tau) - \min(P_\tau)$ for $\tau \in [t-1, t]$. R_t is calculated as the log-range of the variable observed at time τ. $\boldsymbol{\lambda}_t$ is the conditional mean of the range up to time t. It is assumed that the distribution of the innovation term z_t is distributed by a unit-mean density function $f(.)$. In addition, the coefficients in Equation 1 are all positive to ensure the positivity of $\boldsymbol{\lambda}_t$.

We apply Gumbel distributed CARR (1,1) to estimate the volatility (Demiralay and Bayraci, 2015). Table 1 and Figure 2 show the estimation results and time-varying conditional volatility, respectively. In addition, Table 1 contains summary statistics for the volatility series. Kolmogorov-Smirnov (KS) test indicates that innovations fit Gumbel distribution. The findings show that the series are not normal distributed according to the Jarque-Bera test and are stationary according to the Elliott-Rothenberg-Stock (ERS) unit root test. In particular, a significant autocorrelation emerges in all series and the square series, which implies that the mean and variance of each series change over time. Therefore, using a TVP-VAR model with a time-varying variance-covariance structure seems to be an appropriate econometric framework that captures all these empirical properties. Also, Table 1 shows the unconditional correlation matrix across the volatility series over the sampling period.

Table 1. The Estimation WResults of CARR (1,1) Model and Summary Statistics for Volatility Series

Country	ω	α	β	AIC	BIC	LLH	LB	KS	Mean	Variance	Skewness	Ex.Kur	JB	ERS	Q(10)	Q2(10)
AUS	0.004*	0.360***	0.532***	-5.686	-5.650	-652.233	29.412	0.100	0.03	0	4.152***	20.853***	4786.118***	-3.478***	492.798***	366.605***
	(0.002)	(0.104)	(0.145)				[0.773]	[0.224]								
BRA	0.009*	0.406***	0.456***	-4.702	-4.666	-540.052	27.972	0.081	0.051	0.001	4.711***	26.920***	7727.751***	-4.036***	414.213***	307.021***
	(0.005)	(0.111)	(0.157)				[0.828]	[0.456]								
CAN	0.004*	0.425***	0.488***	-5.931	-5.894	-680.110	23.087	0.100	0.027	0	4.357***	24.086***	6232.947***	-3.850***	428.196***	306.106***
	(0.002)	(0.100)	(0.121)				[0.953]	[0.224]								
DEU	0.010*	0.422***	0.378**	-5.112	-5.076	-586.781	31.184	0.072	0.04	0	3.098***	13.527***	2103.048***	-4.045***	352.112***	305.888***
	(0.005)	(0.115)	(0.179)				[0.697]	[0.609]								
EUR	0.009**	0.484***	0.312**	-5.326	-5.290	-611.155	42.537	0.090	0.036	0	3.310***	15.635***	2738.680***	-4.393***	293.774***	250.946***
	(0.004)	(0.113)	(0.154)				[0.210]	[0.326]								
GBR	0.008**	0.431***	0.374**	-5.425	-5.389	-622.443	28.366	0.077	0.034	0	3.542***	17.311***	3323.702***	-4.018***	368.919***	301.250***
	(0.004)	(0.124)	(0.187)				[0.814]	[0.530]								
IND	0.006**	0.407***	0.477***	-5.343	-5.307	-613.132	42.714	0.072	0.036	0	4.423***	24.959***	6661.355***	-4.080***	383.822***	286.046***
	(0.003)	(0.108)	(0.138)				[0.205]	[0.609]								
USA	0.007**	0.421***	0.424**	-5.291	-5.254	-607.143	27.115	0.081	0.037	0	3.210***	14.716***	2448.971***	-4.596***	389.846***	320.912***
	(0.003)	(0.108)	(0.153)				[0.857]	[0.456]								
ZAF	0.014**	0.337***	0.376*	-4.947	-4.911	-567.982	23.185	0.095	0.043	0	3.757***	18.701***	3858.765***	-4.672***	270.617***	284.870***
	(0.007)	(0.112)	(0.225)				[0.951]	[0.271]								
SAU	0.008*	0.230**	0.566***	-5.336	-5.299	-614.052	19.096	0.086	0.043	0.001	7.136***	69.484***	47801.635***	-3.979***	211.209***	28.302***
	(0.004)	(0.080)	(0.164)				[0.991]	[0.388]								
CHN	0.012	0.272***	0.433**	-5.188	-5.151	-587.609	39.203	0.072	0.038	0	1.650***	3.748***	236.977***	-4.695***	142.255***	117.574***
	(0.007)	(0.100)	(0.235)				[0.328]	[0.609]								
JPN	0.011**	0.364***	0.379**	-5.207	-5.170	-594.948	25.862	0.104	0.037	0	3.022***	13.811***	2158.983***	-4.692***	280.676***	269.099***
	(0.005)	(0.110)	(0.189)				[0.894]	[0.182]								
RUS	0.004	0.505***	0.471***	-5.040	-5.003	-570.957	10.089	0.095	0.044	0.001	6.798***	63.787***	40409.18***	-3.951***	248.242***	37.120***
	(0.003)	(0.144)	(0.156)				[0.994]	[0.271]								

Table 1. Continued

	Correlation Matrix												
	AUS	**BRA**	**CAN**	**DEU**	**EUR**	**GBR**	**IND**	**USA**	**ZAF**	**SAU**	**CHN**	**JPN**	**RUS**
AUS	—												
BRA	0.895***	—											
CAN	0.961***	0.892***	—										
DEU	0.850***	0.765***	0.853***	—									
EUR	0.852***	0.777***	0.863***	0.968***	—								
GBR	0.888***	0.812***	0.889***	0.919***	0.928***	—							
IND	0.917***	0.881***	0.921***	0.829***	0.837***	0.843***	—						
USA	0.901***	0.832***	0.940***	0.869***	0.873***	0.880***	0.842***	—					
ZAF	0.850***	0.829***	0.878***	0.809***	0.818***	0.848***	0.832***	0.868***	—				
SAU	0.695***	0.692***	0.688***	0.591***	0.599***	0.607***	0.712***	0.607***	0.636***	—			
CHN	0.294***	0.324***	0.324***	0.358***	0.377***	0.322***	0.305***	0.351***	0.401***	0.119***	—		
JPN	0.829***	0.786***	0.863***	0.787***	0.809***	0.786***	0.822***	0.859***	0.829***	0.592***	0.378***	—	
RUS	0.424***	0.397***	0.459***	0.523***	0.513***	0.427***	0.465***	0.425***	0.444***	0.325***	0.321***	0.478***	—

Notes: * p < .10, ** p < .05, *** p < .01 Volatilities are based on Gumbel distributed CARR(1,1) model. AIC: Akaike Information Criteria, BIC: Bayes Information Criteria, LLH: Log-likelihood, LB: Ljung-Box, KS: Kolmogorov-Smirnov. The values in parenthesis are standard errors. The corresponding p-values with the test statistics are in brackets. Skewness, Kurtosis, and JB: Jarque and Bera test for normality; ERS: Elliott-Rothenberg-Stock unit-root test; (20) and $Q2(20)$: weighted portmanteau test. Bold and italic entries are corresponding probabilities.

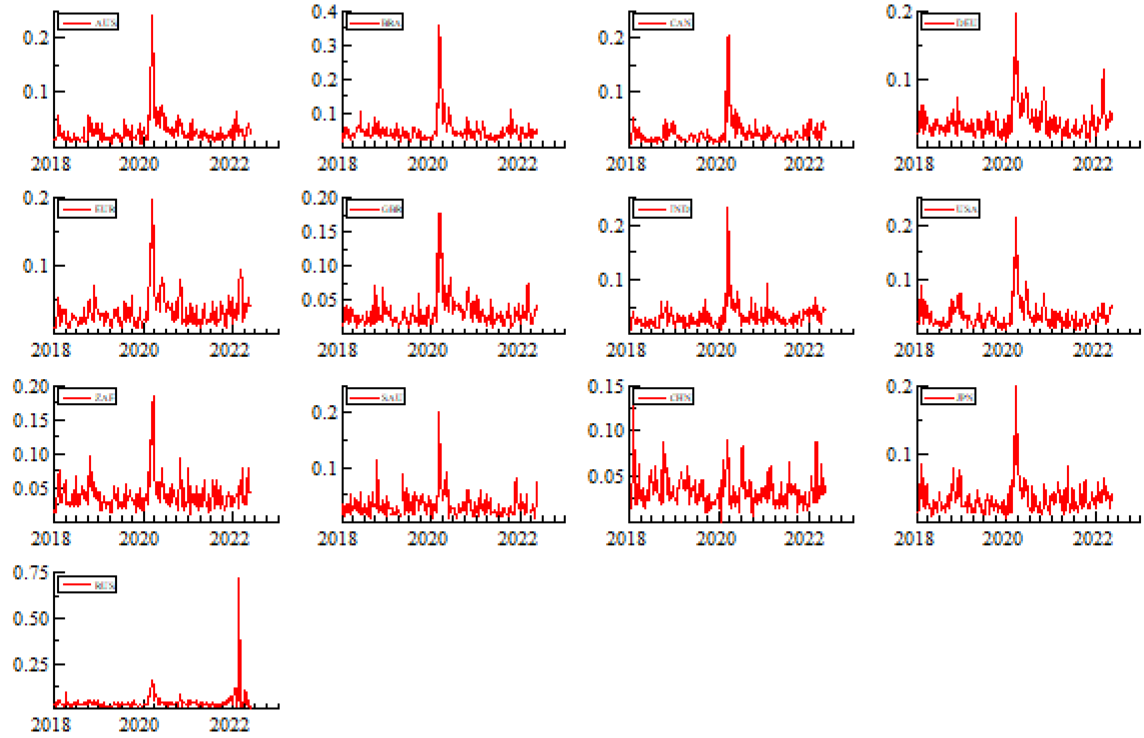

Figure 1. Log-Range Series

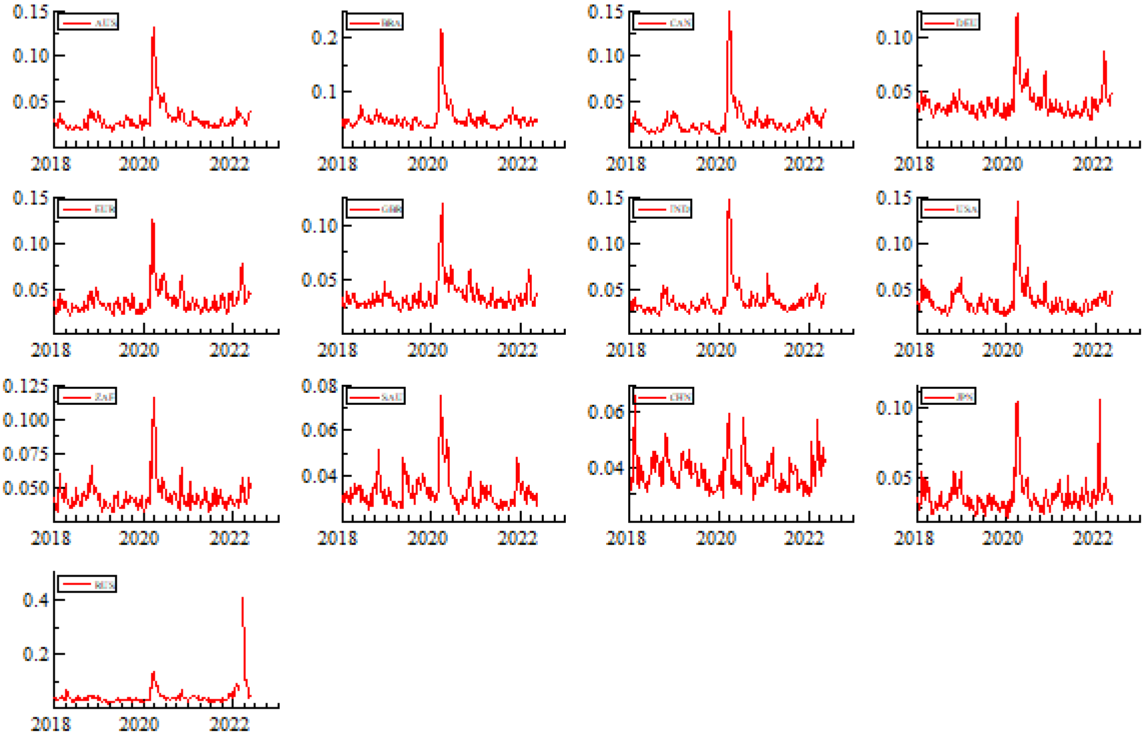

Figure 2. Volatility Series Based on Gumbel CARR(1,1)

3. TVP-VAR-Based Connectedness Approach

The connectedness approach proposed by Diebold and Yilmaz (2009, 2012, 2014) is a method that reveals the interconnections in a specified network and provides both static and dynamic time series network analysis. This approach has been widely used lately, as it provides researchers with the opportunity to make inferences. It is a successful computational method that estimates the dynamic interconnectedness between variables, this is particularly important to capture cross-market spillovers in times of market turmoil and crises. The static approach adapts a Vector Autoregressive (VAR) model over the entire dataset, while the dynamic approach is estimated with a rolling window VAR approach. In this paper, we use a dynamic connectedness approach based on Time-Varying Parameter Vector Autoregressions (TVP-VAR) by Antonakakis et al. (2018, 2020). They propose a method to prevent data loss, including the working sample data used in the rolling window VAR method. According to Bouri et al. (2021) TVP-VAR-based connectedness approach includes the following additional advantages: “*(i) outlier insensitivity caused by the underlying Kalman filter, (ii) there is no need to choose the rolling window size arbitrarily, (iii) no loss of observation and (iv) can also be used for low-frequency datasets”*.

Antonakakis et al. (2020) use Kalman filter estimation with forgetting factors, as in Koop and Korobilis (2014). Thus, they enhanced Diebold and Yilmaz's (2014) connectedness approach using the TVP-VAR method by allowing the variance-covariance matrix to vary. We estimate the TVP-VAR model to investigate the time-varying volatility linkage among the stock markets. The TVP-VAR(1) model, determined to be the most suitable by Bayes Information Criteria (BIC), is as follows.

$$z_t = \mathrm{A}_t z_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{2}$$

$$vec(A_t) = vec(A_{t-1}) + \upsilon_t \qquad \upsilon_t \sim N(0, \mathrm{S}_t) \tag{3}$$

where z_t, z_{t-1} and ϵ_t represent $k \times 1$ dimensional vectors, and A_t and Σ_t are $k \times k$ dimensional matrices, $vec(A_t)$ and υ_t are $k^2 \times 1$ dimensional vectors. S_t are time-varying variance-covariance matrices of which dimension is $k^2 \times k^2$.

Diebold-Yilmaz’s approach is based on the Generalized Forecast Error Variance Decomposition (GFEVD) analysis. Thus, we need to transform TVP-VAR into TVP-VMA since Wold representation theorem that is $y_t = \sum_{h=0}^{\infty} \mathrm{A}_{ht} \epsilon_{t-h}$ where $\mathrm{A}_0 = I_k$. So, we can predict pairwise directional connectedness using the h-step forward GFEVD. In other words, the influence of a shock in variable j on variable i is computed as:

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\sum_{h=0}^{H-1} \left(\epsilon_i^T A_{ht} \Sigma_t \epsilon_j\right)^2}{\left(\epsilon_i^T \Sigma_t \epsilon_j\right) \sum_{h=0}^{H-1} \left(\epsilon_i^T A_h \Sigma_t A_{ht}^T \epsilon_i\right)} \tag{4}$$

with $\sum_{j=1}^{m} \tilde{\phi}_{ij,t}^{g}(H) = 1$ and $\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}^{g}(H) = k$. Thus, the connectedness measures of Diebold-Yilmaz (2012, 2014) via GFEVD are calculated as follows

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \tag{5}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) \tag{6}$$

$$NET_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) - \sum_{i=1, i\neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) = TO_{jt} - FROM_{jt} \tag{7}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt} \tag{8}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}^{g}(H) - \tilde{\phi}_{ji,t}^{g}(H) \tag{9}$$

Equation 5 (Total Directional Connectedness to Others - TO): Represents the total effect of a shock in j on all other variables.

Equation 6 (Total Directional Connectedness from Others - FROM): Shows the cumulative effect of all other variables on the j variable.

Equation 7 (Net Total Directional Connectedness - NET): Subtracting the effect of variable j on others from the effect of others on j shows whether the variable is a net shock transmitter or receiver. If $NET_{jt} > 0$ ($NET_{jt} < 0$), the variable j is a net transmitter of shocks ($receiver$) – and therefore drives the network ($driven\ by$).

Equation 8 (Total Connectedness Index – TCI): Exhibits the average effect of a variable on all others. If TCI is relatively high, it means that the network is significantly interconnected. Thus, market risk is high, as the shock in one variable will affect the others. A low TCI indicates that most variables are fairly independent of each other, meaning that a shock in one variable will not cause the other variables to adjust. So, it will result in lower market risk.

Equation 9 (Net Pairwise Directional Connectedness - NPDC): Offers information about the bilateral relationship between j and i via subtracting the impact variable j has on variable i by the influence variable i has on variable j. If $NPDC_{ij,t} > 0$ ($NPDC_{ij,t} < 0$), it means that the variable j dominates (is dominated by) the variable i.

4. Empirical Findings

Antonakakis et al. (2020) utilize forgetting factors provided by Koop and Korobilis (2014), where the TVP-VAR forgetting factor is 0.99 and the EWMA forgetting factor is 0.96. Therefore, we consider the same forgetting factors' values. Moreover, we apply the TVP-VAR model with Minessota Prior which is applied in the studies by Antonakakis et al. (2020) and Korobilis and Yilmaz (2018). Our findings are summarized in the following sections

4.1. Total and Dynamic Connectedness Index

Table 2 reports the averaged connectedness measures of two panels, without and with RUS. While the main diagonal of the matrices (blue) in tables show own-variance shares of shocks, off-diagonal elements reflect the interaction across financial assets.

There is high connectedness in both groups. While the TCI is 79.91% in the first panel, the average TCI increases to 81.44% with the addition of RUS. The reason that we examine interconnectedness by excluding the Russian market is to show that the volatility pass-through between developed and high-capital markets is high. However, it is noteworthy in the first panel that the markets of ZAF, SAU, and CHN are less affected by this interconnection. Apart from BRA, volatility receivers in the first panel, ZAF, SAU, CHN, and JPN markets are also receivers in the second panel. We see that the addition of the RUS does not affect the TCI much. In the second panel, there is a volatility contagion from western markets to eastern markets (excluding IND). In fact, the return, range, and volatility correlation[2] values show that the SAU, CHN, and RUS markets have a statistically significant positive correlation with other markets but are of relatively small value. The connectedness results also support this situation.

[2] In this paper, we present only the unconditional correlation between volatilities in Table 1. The correlation of log-returns and log-ranges are available upon request.

Table 2. Average Connectedness Table

Panel 1: TCI without RUS

	AUS	BRA	CAN	DEU	EUR	GBR	IND	USA	ZAF	SAU	CHN	JPN	FROM
AUS	15.08	8.42	12.57	8.83	9.68	9.3	9.36	9.56	6.42	2.88	1	6.89	84.92
BRA	9.91	21.85	10.48	7.22	7.74	8.15	9.89	8.16	5.98	3.17	1.49	5.96	78.15
CAN	11.08	8.1	14.54	8.94	9.9	9.39	8.88	10.84	6.71	2.59	1.25	7.77	85.46
DEU	9.21	6.49	10.21	15.32	13.52	11.45	7.27	10.05	6.17	1.95	1.24	7.12	84.68
EUR	9.22	6.51	10.51	12.47	14.73	11.51	8.06	9.81	6.5	2.03	1.29	7.36	85.27
GBR	9.79	6.27	10.87	11.28	12	15.58	7.87	9.5	7.47	1.93	0.81	6.63	84.42
IND	10.57	8.49	10.85	8.91	9.84	9.01	17.28	7.35	6.17	3.78	0.84	6.89	82.72
USA	9.32	7.1	12.61	9.27	10.17	8.92	7.3	15.33	7.4	1.88	1.86	8.85	84.67
ZAF	8.51	7.25	10.38	8.8	9.57	9.93	7.31	9.37	14.68	2.57	3.02	8.63	85.32
SAU	7.77	6.56	7.25	6.11	6.42	5.03	7.31	5.3	5.73	37.49	1.22	3.8	62.51
CHN	3.82	6.46	5.92	5.49	6.5	5.51	4.65	6.65	5.05	1.68	43.13	5.14	56.87
JPN	8.47	6.22	11.14	9.2	10.09	8.35	7.83	10.55	7.59	1.9	2.59	16.07	83.93
TO	97.67	77.86	112.8	96.52	105.43	96.56	85.74	97.15	71.18	26.37	16.6	75.05	958.92
Inc.Own	112.75	99.71	127.33	111.85	120.16	112.14	103.02	112.47	85.86	63.85	59.73	91.12	**TCI**
NET	12.75	-0.29	27.33	11.85	20.16	12.14	3.02	12.47	-14.14	-36.15	-40.27	-8.88	**79.91**

Panel 2: TCI with RUS

	AUS	BRA	CAN	DEU	EUR	GBR	IND	USA	ZAF	SAU	CHN	JPN	RUS	FROM
AUS	13.48	7.86	11.5	8.56	9.28	8.71	8.81	8.83	6.15	2.89	1.37	6.79	5.76	86.52
BRA	9.01	20.31	9.67	7	7.48	7.61	9.39	7.6	5.65	3.28	1.74	5.73	5.52	79.69
CAN	9.78	7.47	13.07	8.7	9.54	8.86	8.42	9.98	6.46	2.6	1.68	7.37	6.07	86.93
DEU	8.61	6.36	9.9	14	12.27	10.36	6.54	9.89	6.27	2.06	1.47	7.18	5.07	86
EUR	8.71	6.45	10.13	11.32	13.57	10.47	7.45	9.53	6.45	2.11	1.59	7.22	4.98	86.43
GBR	8.88	6.05	10.44	10.32	11.05	14.27	7.27	9.26	7.32	2.04	1.04	6.7	5.35	85.73
IND	9.52	8.17	10.04	8.14	9.01	8.03	16.11	6.89	5.99	3.75	1.16	6.73	6.46	83.89
USA	8.4	6.57	11.69	9.18	9.94	8.61	6.95	14.18	7.09	2.01	2.13	8.53	4.72	85.82
ZAF	7.68	6.68	9.67	8.39	9	9.1	6.81	8.75	13.98	2.68	3.32	8.4	5.55	86.02
SAU	7.29	6.17	7.16	6.49	6.95	5.48	7.48	5.22	5.68	31.64	1.17	4.22	5.07	68.36
CHN	3.89	6.64	5.84	4.9	5.97	4.83	4.65	6.46	5.04	1.67	37.91	5.12	7.08	62.09
JPN	7.65	5.8	10.19	8.84	9.57	7.73	7.24	9.92	7.41	2.03	3.05	15.19	5.39	84.81
RUS	6.8	7.24	8.91	7.72	7.86	7	7.49	6.74	6.23	2.54	2.51	5.36	23.62	76.38
TO	96.23	81.46	115.15	99.56	107.92	96.78	88.5	99.08	75.74	29.66	22.25	79.35	67.01	1058.67
Inc.O	109.7	101.76	128.22	113.56	121.5	111.04	104.61	113.26	89.72	61.3	60.15	94.53	90.63	**TCI**
NET	9.7	1.76	28.22	13.56	21.5	11.04	4.61	13.26	-10.28	-38.7	-39.85	-5.47	-9.37	**81.44**

Notes: Results are based on a TVP-VAR (1) model and a 10-step-ahead GFEVD. cTCI: corrected TCI

Table 2 shows the aggregate results for the entire period and discards the time-varying spillover effects. However, from a practical standpoint, assuming static spillovers would be unrealistic given the fast-changing financial landscape and macroeconomic environment, we use the dynamic connectedness of the network that fluctuates considerably over time. Figure 3 illustrates the dynamic connectedness throughout the whole period. So, one can identify specific episodes that alter the connectedness structure across indices over time. The dynamic structure in both panels shows that TCI tends to converge to the average value after the crises. TCI reaches its highest value 90.94% in March 2020, when the Covid-19 pandemic was declared, and decreases until the beginning of 2022. Dynamic TCI moves together in both panels. However, the TCI including RUS reaches the connectedness value almost at the beginning of the pandemic in the last week of January 2022, when the tension between Russia and Ukraine increased. In the third week of February 2022, when the Russia-Ukraine war started, it was 74.03% in TCI Panel 1, while it was 87.98% in Panel 2. Thus, the effect of risk spillover originating from the RUS can be seen visually. Moreover, it is noteworthy that the TCI in Panel 1 deviates slowly at the beginning of the war. This shows that the persistence of war-related connectedness is lower than during the Covid-19 pandemic.

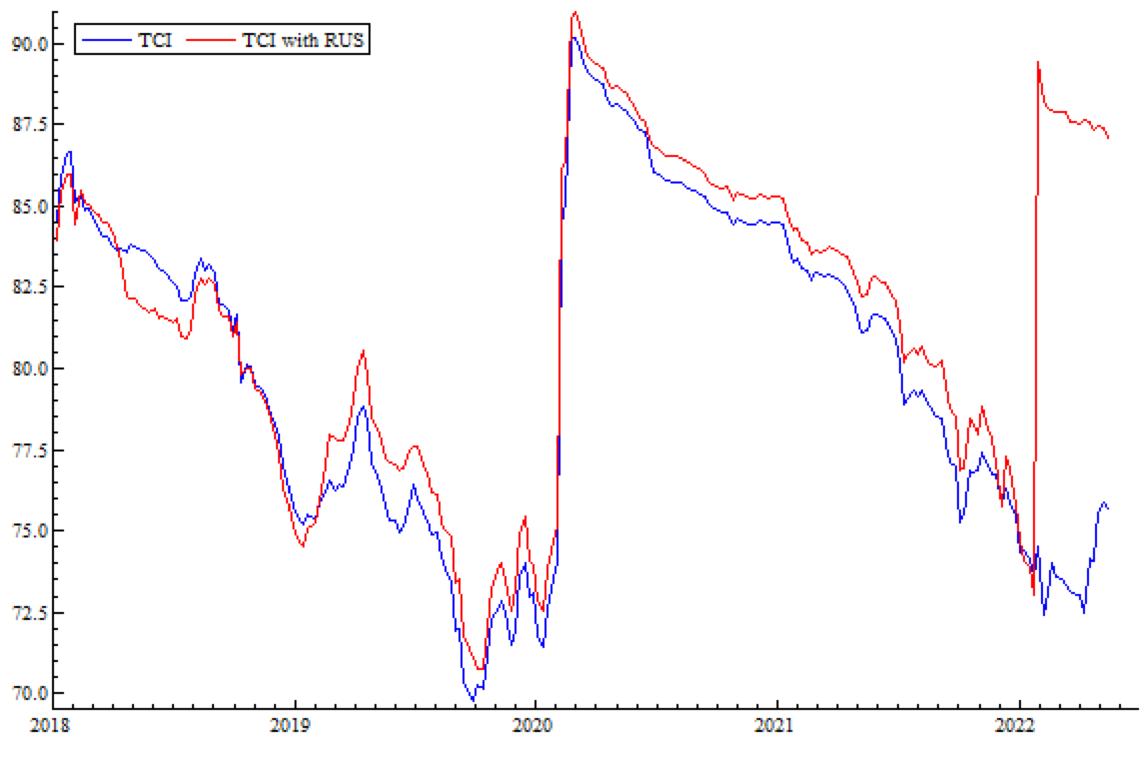

Figure 3. Dynamic Total Connectedness.
Results are based on a TVP-VAR (1) model and a 10-step-ahead GFEVD.

4.2. Net Total Connectedness

Figure 4 presents the Net Total Directional Connectedness (NET) of the system. NET practically shows the difference between the transmitting and the receiving shocks of each index considering the entire network. The positive values show a net-transmitting role of the index and negative values show the period when the index is a net receiver of shocks from others.

The figures show that the SAU has been a volatility receiver for the entire period. We also see that the period when SAU was exposed to the most volatility spillover was the beginning of the Russia-Ukraine War. The AUS, CAN, USA and JPN markets have been highly volatility receiver during the war. Interestingly, DEU, EUR and CHN have been very high-risk transmitters when the war began. While the RUS was a risk receiver for the entire period except for the onset of Covid-19, it became the highest risk transmitter among the markets with the beginning of the war. However, we observe that the effect of the shock caused by the war disappeared in a short time. Also, we see that all markets converged to their average NET values given in Panel 2 part of Table 2 in May 2022.

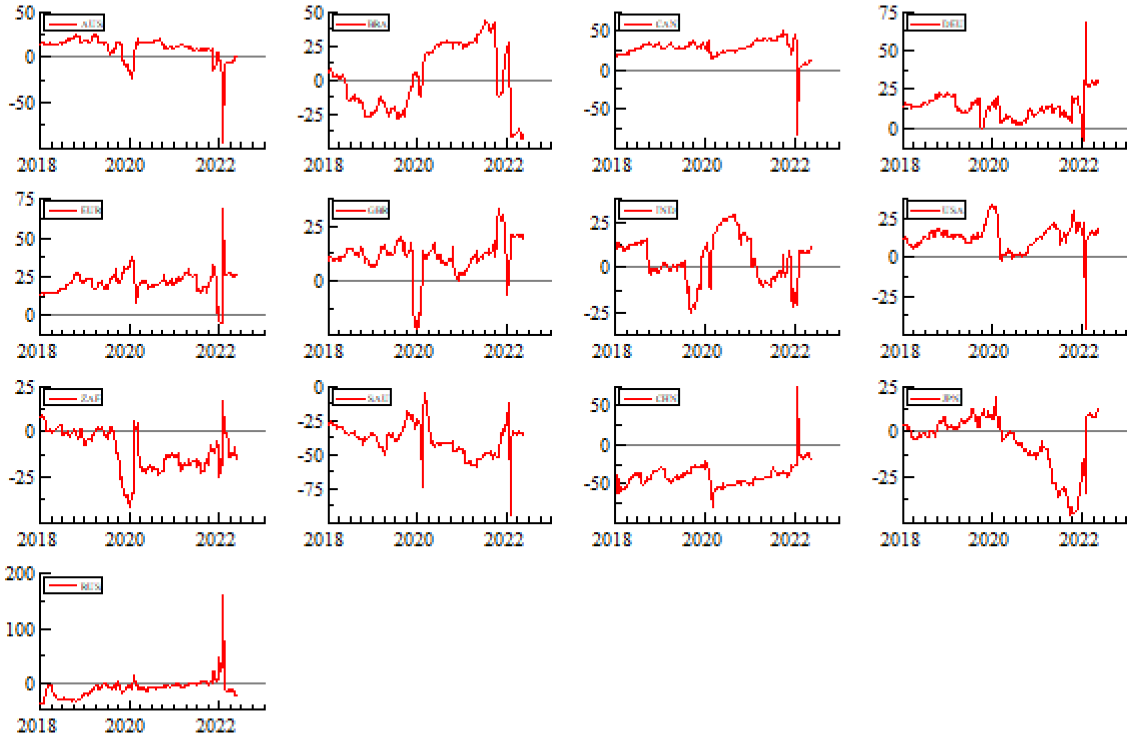

Figure 4. Net Total Directional Connectedness.

4.3. Net Pairwise Directional Connectedness

Even though the net spillovers explicitly depict a clear picture of the spillovers over time, they do not show associated pairwise dynamics between variables. Figure 5 displays the Net Pairwise Directional Connectedness (NPDC) measures of spillovers. In Figure 5 we only present the NPDC between the RUS and other markets. At first glance, we see that the RUS dominates the SAU and CHN markets. However, it turns out that while the war influenced the SAU, there was no effect on the CHN. Interestingly, after the Covid-19 pandemic, the RUS market became a sender of stress to the JPN and ZAF markets. However, the average NPDC values in Table 3 show that the RUS market dominates only the SAU, CHN and JPN markets. In all markets except the CHN, the effects of war appear, and they receive risk from the RUS market.

Table 3. Average NPDC Table

	AUS	BRA	CAN	DEU	EUR	GBR	IND	USA	ZAF	SAU	CHN	JPN
NPDC	1.05	1.72	2.84	2.64	2.87	1.65	1.03	2.02	0.68	-2.53	-4.57	-0.03

Figure 6 shows the pass-throughs across the entire network to support the NPDC results. Circles in blue indicate volatility transmitters, and oranges indicate receivers. The large circle diameter shows that the related market dominates (is dominated by) the other. We see that EUR and CAN markets are large transmitters, and SAU and CHN markets are large receivers. Figure 6 more clearly illustrates the difference between eastern (excluding IND) and western markets.

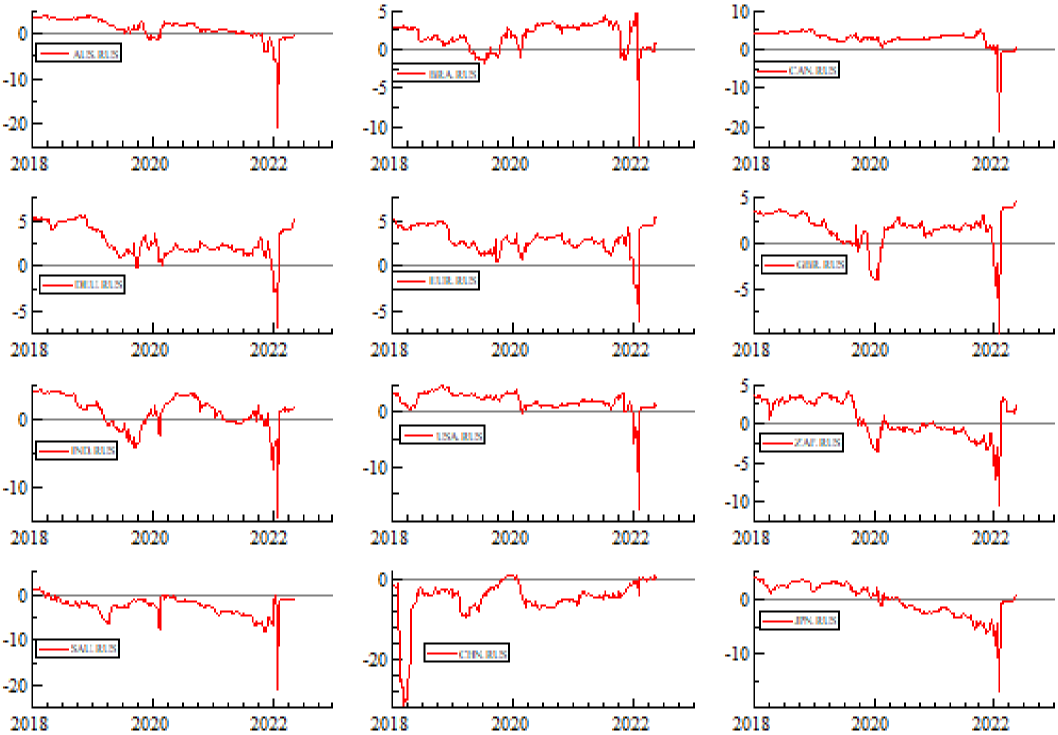

Figure 5. Net Pairwise Connectedness between RUS and Other Indices.

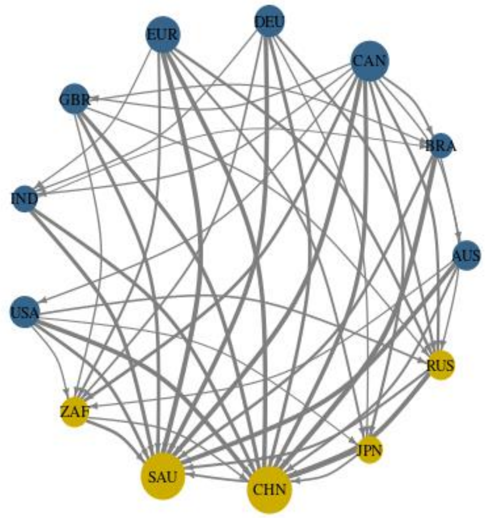

Figure 6. Network Plot

4.4. Brief Discussion

Our findings for Covid-19 pandemics are supported by the studies by Guo et al. (2021), Davidovic (2021), and Li et al. (2021). The findings of the study by Guo et al. (2021) show that the pandemic enlarges contagion channels in the international financial system. Moreover, Davidovic (2021) indicates international financial markets are more integrated, and risk contagion increases during the pandemic. Lastly, Li et al. (2021) examine the risk contagion among sixteen major stock markets in the world during the COVID-19 pandemic by using the realized volatility connectedness approach. Like our findings, they find empirical evidence that the COVID-19 epidemic significantly increases the risk of contagion effects in international stock markets.

As in the study of Umar et al. (2022), we find that Russian markets are the net transmitters of shocks, and the war affected the volatility connectedness among the global markets. Also, our findings have similarities with the result of Yousaf et al. (2022) which indicates Chinese market is neutral when the war began.

5. Conclusion

We examine the spillover between volatilities obtained from the CARR process with the TVP-VAR-based Diebold-Yilmaz approach. We estimate CARR the conditional distributions of innovations using the Gumbel distribution. Moreover, we investigate the impact of the Ukraine-Russia War on global markets as an example. For this purpose, we consider the Russian stock market index and indices selected from among the twenty largest stock exchanges by asset size to perform the connectedness analysis. We apply Gumbel distributed CARR (1,1) to estimate the volatilities. The summary statistics for the volatility series indicate that innovations fit the Gumbel distribution by the Kolmogorov-Smirnov test and the series are not normally distributed according to the Jarque-Bera test. Also, the obtained volatility series are stationary according to the Elliott-Rothenberg-Stock unit root test. We also observe that a significant autocorrelation emerges in all series and the square series. In conclusion, using a TVP-VAR model with a time-varying variance-covariance structure is an appropriate econometric framework to capture all these empirical properties. In TVP-VAR analysis, we calculate averaged connectedness measures of two panels, without and with RUS, and find that the TCI is 79.91% in the first panel, the average TCI increases to 81.44% with the addition of RUS. It is noteworthy in the first panel that the markets of ZAF, SAU, and CHN are less affected by this interconnection. We see that the addition of the RUS does not affect the TCI much. In the second panel, there is a volatility contagion from western markets to eastern markets (excluding IND). The RUS dominates the SAU and CHN markets according to NPDC. However, it turns out that while the war influenced the SAU, there was no effect on the CHN. Interestingly, after the Covid-19 pandemic, the RUS market became a sender of stress to the JPN and ZAF markets. However, the average NPDC values show that the RUS market dominates only the SAU, CHN, and JPN markets. In all markets except the CHN, the effects of war appear, and they receive risk from the RUS market.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher’s Conflict of Interest
There is no potential conflicts of interest in this study.

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