

THE ROLE OF THE CEE REGION'S BANKING SECTOR IN THE TIME OF THE RUSSO-UKRAINIAN WAR: MEASURING VOLATILITY SPILLOVERS

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ABSTRACT

In this paper, I investigate the volatility spillovers of the European banking network in 21-22. Applying the *Diebold-Yilmaz* framework to the daily stock return, which identified volatilities for 14 European banks, I analyse the impact of the first 100 days of the Russo-Ukrainian War on the banking sector. The empirical results suggest that the volatility-connectedness of the system reaches its maximum at a time of war. Similar to the earlier empirical literature, I find that, in calm periods, large banks play a critical role in volatility risk transmission. However, I conclude that, during the first 100 days of the Russo-Ukrainian War, the key participants in the financial network were institutions from the CEE region. My results suggest that, considering the banking network's macro and group-aggregated level volatility connectedness, an early-warning system to detect troubled financial institutions should be built.

JEL codes: C32, G01, G12, G15, G21

Keywords: volatility spillover, banking sector, Russo-Ukrainian war, CEE region

1 INTRODUCTION

Network analysis of the financial institution (FI) system has become widely recognised as a critical regulatory issue over the past decade. Connections and spillovers between FIs play a crucial role in systemic risk assessment. Furthermore, during crises, the strength of the connections sharply increases. Risk spills over across institutes, as happened during the Global Financial Crisis (GFC) of 2007-2009, the European Sovereign Debt Crisis (ESDC), and more recently during the Covid-19 (C19) turmoil and the Russo-Ukrainian War (RUW) (Diebold and Yilmaz, 2014). These events highlighted the importance of analysing the connections and spillover channels between financial institutions. For this reason, regu-

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lators need to monitor the structural changes in financial networks and identify the systemically important financial institutions (SIFIs), as the key participants in the financial institutions' network.

Recently, several empirical frameworks (quantitative methods) have appeared, aiming to calibrate the linkages among FIs and observe systemic risk. *Bisias et al.* (2012) identified more than 30 quantitative systemic risk measures in economics and finance literature. Their survey classifies them into six groups, one of which is a network-based approach.

On the empirical side of the systemic risk modelling from the network perspective, several measurements have recently been developed to quantify the connections between FIs. The most widespread methods are the Granger causality network (*Billio et al.*, 2012), the delta conditional value-at-risk (ΔCoVaR) proposed by *Tobias and Brunnermeier* (2016), and the marginal expected shortfall (MES) (*Acharya et al.*, 2012). Besides them, *Brownlees and Engle* (2017) designed the conditional capital shortfall index (SRISK), and numerous studies appeared based on the Vector autoregressive model-based Diebold-Yilmaz (DY) framework (DY, *Diebold–Yilmaz*, 2009; 2012; 2014).

We can group these measures in several ways. One differentiates the price-based systemic risk methods from those that incorporate book values. The first includes the ΔCoVaR and the MES, while the second includes SRISK, the leverage ratio, and the CAPM beta times market capitalization (*Benoit et al.*, 2017).

Besides that, the existing empirical literature on systemic risk can be divided into two broad approaches. The first measures the financial institutions' overall systemic risk in a univariate framework. These models (ΔCoVaR , MES, and SRISK) cannot consider all connections between the FIs in the network. The second group of studies focused on connections and spillovers between the FIs as a potential source of systemic risk using network-related methods (Granger-causality and DY framework). These methods make it possible to capture the linkages on different levels of the network and consider the global connectivity of all system participants.

Of the relevant systemic risk methods, the Diebold-Yilmaz framework has several favourable properties. First, unlike Granger causality network analysis (*Billio et al.*, 2012), the DY framework estimates weighted connections (*Diebold and Yilmaz*, 2012). Second, ΔCoVaR (*Tobias and Brunnermeier*, 2016) and MES (*Acharya et al.*, 2012) are related to the directional connectedness indices of *Diebold and Yilmaz* so, unlike the DY framework, they cannot track any association between individual firms (*Diebold and Yilmaz*, 2015).

In recent years, the literature has highlighted the positive implications of these network models. Due to its favoured attributes, the DY framework has often been

used to analyse the spillovers of financial institutions through stock price volatilities ((Diebold és Yilmaz, 2014; Baruník és Krehlík, 2018), or the linkages between FIs and sovereign bonds (Alter and Beyer, 2014 and Demirer et al., 2018) or sovereign credit default swap (CDS) prices ((Bratis et al., 2020; Greenwood-Nimmo et al., 2019).

In addition, the DY framework has been applied to networks of different asset classes such as equities (Baruník et al., 2016), bonds (Claeys and Vasíček, 2014), exchange rates (Bubák et al., 2011), commodity prices (Kang et al., 2017), crypto currencies (Moratis, 2021), or across asset classes (Kurka, 2019; Wang et al., 2016).

Focusing on the FI network, Diebold and Yilmaz (2014) first applied the framework to systemic risk modelling. They used the daily realised volatility time series to examine the sensitivity of the connections across major U.S. FIs. They focused on the four key events of GFC and illustrated the network on specific days with network snapshots. Diebold and Yilmaz (2015) extended this analysis by examining the spillover channels of the volatility network of major American and European financial institutions that emerged during the GFC and the ESDC. They found the following results related to the two continent's bank systems: prior to the Lehman Brothers' collapse, realized volatility spillovers² primarily flowed from U.S. financial institutions to their European counterparts. However, after Lehman Brothers' bankruptcy in September 2008, the financial crisis evolved into a worldwide phenomenon, causing volatility spillovers and linkages across the Atlantic to become two-way, with a notable decrease in net spillover from the U.S. to Europe. Demirer et al. (2018) applied a LASSO (least absolute shrinkage and selection operator) estimated VAR model to extend the number of financial institutions investigated and analyse global bank network connectedness. They examined a network comprising the top 150 banks between 2003 and 2014 and concluded that global bank spillovers have a strong geographic component.

The empirical literature on European systemic risk modelling from a network perspective has become increasingly developed in recent years. One of the first studies by Paltalidis et al. (2015) found that the European banking sector is highly connected, which causes a risk of financial contagion. A few years later, Dreassi et al. (2018) examined the credit risk spillover based on the CDS spreads between the European banks and insurance companies over the GFC and ESDC. They concluded that, for banks, their funding and income diversification and, for insurance companies, their size and leverage play the key role in risk spillover. Shahzad et al. (2019) differentiate large and small banks in the network and highlight that

2 volatility spillover: a shock in a financial institution's volatility affects the other institution's volatility

large institutions are the transmitters of the network, and the small ones play the role of receiver. Besides that, the network connections depend on the market's state. Using an advanced network method³, *Foglia and Angelini* (2020) examined the tail risk connections between FIs in the Eurozone. They show that risk spillover is more substantial during crisis periods. Besides that, they show that the banks are the key participants in the system. *Torri et al.* (2021) strengthened the earlier results, highlighting the strong connections between the institutions of the European banking sector. *Borri and Di Giorgio* (2021) examined the role of the largest European banks in the FI network, and show that larger banks contribute more to contagion than smaller ones. Of the European bank network studies, only a few had a Central and Eastern Europe (CEE) regional focus, mainly related to the Hungarian market (*Berlinger et al.*, 2011; 2016; *Bodnár*, 2021).

Despite the large number of recent network-based systemic risk modelling studies and the diverse methods used, the deeper structure of the FI networks (analysing at both micro and other aggregated levels) during crisis periods has yet to be investigated. Besides that, more studies that aim to identify the key participants of the system and analyse the dynamics of their connections and spillovers during turbulent periods and different crises need to be carried out. It is essential that regulators monitor any abrupt changes in the financial network, understand the dynamics of the network at different levels and identify the role of the key participants in the system.

To address this situation, in this paper I characterise the static and dynamic volatility connectedness⁴ of 14 European financial institutions via the DY framework before and during the Russo-Ukrainian War. My analysis differs from previous studies in its selected time period and the FIs investigated. I examine the connections between the most significant and medium western European banks and four financial institutions from the CEE region.

My research makes a twofold contribution to the systemic risk literature. Firstly, I aim to investigate the spillovers between FIs in different regions of Europe. Despite numerous studies analysing the volatility spillover between financial institutions in Europe, to the best of my knowledge, this is the first research focusing on the role of the CEE region's financial institutions in the network. Secondly, I provide fresh evidence of volatility connectedness during the RUW. Although many papers investigated the spillovers of the bank network during different crisis periods (GFC, ESDC, C19), none of them examined the dynamics of the network and the key participants before and during the war.

3 TENET framework

4 volatility connectedness: the strength of the linkages in the volatility network

This paper proceeds as follows. In *Section 2*, I briefly outline the Diebold-Yilmaz framework. I present the dataset in *Section 3*. In *Section 4*, I provide dynamic and static characterisations of the volatility-connectedness of the European financial institutions during the RUW. Finally, I conclude in *Section 5*.

2 DIEBOLD-YILMAZ FRAMEWORK

I use the framework devised by Diebold and Yilmaz (2014) to estimate the network of the selected financial institutions. Following the seminal paper (Diebold and Yilmaz, 2009; 2014), the network and spillover measures are based on VAR(p) model coefficient and covariance matrix estimation (Sims, 1980) and its forecast error variance decompositions (FEVD).

The framework is based on the concept that, for every time series of the network, we can calculate the forecast error variance based on the estimated VAR(p) model coefficient and covariance matrix. This variance is related to its own and other time series shocks. Due to the VAR(p) model identification, the shares of own and other time series' shocks can be calculated. In the last step of the process, the forecast error variance decompositions can be summarized in a spillover table, which we refer to hereafter as the DY spillover table.

The first step of the estimation process is to specify a stationary VAR(p) model with J time series using the following equation:

$$\mathbf{y}_t = \sum_{i=1}^p \mathbf{B}_i \mathbf{y}_{t-i} + \mathbf{u}_t \quad (1)$$

where \mathbf{Y}_t is a $J \times 1$ vector of the time series, $\boldsymbol{\beta}_i$ is an $J \times J$ autoregressive coefficient matrix, and lastly $\boldsymbol{\varepsilon}_t$ is an $J \times 1$ vector of error terms. It has a zero mean with a Σ covariance matrix. The VAR(p) process is assumed to be stable and stationary, while the covariance matrix Σ is needed to be positive definite with bounded largest eigenvalue (Lütkepohl, 2013).

To estimate the DY framework's most important element, the DY spillover table, we need to estimate the coefficient matrices $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \dots, \boldsymbol{\beta}_p$ and the error covariance matrix Σ efficiently. The $\boldsymbol{\beta}_i$ coefficient matrices reveal the temporal dependence between the time series and Σ reveals the contemporaneous linkages among them (Diebold and Yilmaz, 2014).

The starting point for the DY framework to transform the time series in the VAR(p) in Eq. 1 into its vector moving average (VMA) representation using the *Wold* theorem to derive the following equation:

$$\mathbf{y}_t = \sum_{i=0}^{\infty} \mathbf{A}_i \boldsymbol{\varepsilon}_{t-i} \quad (2)$$

where A_i is an $J \times J$ moving average coefficient matrix (Diebold and Yilmaz, 2012). As Diebold and Yilmaz (2014) emphasised, the calculated moving average coefficients and the estimated error covariance matrix (or its nonlinear transformations, such as impulse response functions (IRF) or forecast error variance decompositions (FEVD) are the keys to understanding the dynamics of the time series network.

FEVD allow us to calculate the fraction of the H step-ahead error variance in forecasting Y_i (Y_i^H) that is due to shocks to other time series such as Y_j , to which we will hereafter refer as a spillover between Y_i and Y_j . Generally, in the DY framework the measures of spillovers between the time series are given by the FEVD of the VAR(p) model. Unfortunately the calculation of the FEVD requires orthogonal innovations, but the VAR innovations are generally contemporaneously correlated (Diebold and Yilmaz, 2012; 2014).

There are two widely used approaches in the early DY framework-related papers for deriving the variance decomposition. The first method uses the *Cholesky* factor orthogonalisation of the covariance matrix Σ , which generates orthogonalised innovations. The weakness of this decomposition is that its results in an order-dependent FEVD (Diebold and Yilmaz, 2012).

The other approach uses the generalised VAR framework of *Koop et al.* (1996) and *Pesaran and Shin* (1998), which allows correlated shocks. As a result, this second method produces an order-independent FEVD. In the empirical DY network studies, applying the second method is more widespread.

The generalised FEVD can be calculated in the following way:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Phi A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_j)^2} \quad (3)$$

where σ_{jj} is the j -th diagonal element of the error term's covariance matrix Σ , A_h is the moving average coefficient matrix multiplying the h -lagged shock vector in the Wold's moving average representation (Eq. 2) and e_i is a selection vector. The numerator in Eq. 3. represents the contribution of shocks in variable Y_j to the H -step FEVD of time series Y_i . The denominator is the forecast error variance of the time series Y_i .

Unfortunately, the sum of the contributions to the variance of the forecast error is not necessarily one because, in the general FEVD, the shock terms are not orthogonalised (Diebold and Yilmaz, 2012). Normalisation is therefore required, which we calculate in the following way:

$$\theta_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^J \theta_{ij}^g(H)} \quad (4)$$

The generalised FEVD is used to construct the several systemic/network-connectedness measures of the DY framework (Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014)). First, the sum of directional spillovers to time series Y_i FROM all other time series (FROM spillover index $S_{i\leftarrow*}^g(H)$) is defined with the following equation:

$$S_{i\leftarrow*}^g(H) = \frac{\sum_{k=1, k \neq i}^J \theta'_{ik}(H)}{\sum_{k=1}^J \theta'_{ik}(H)} * 100 = \frac{\sum_{k=1, k \neq i}^J \theta'_{ik}(H)}{K} * 100 \quad (5)$$

Second, we are interested in the sum of the shocks transmitted by time series Y_i TO other time series (TO spillover index $S_{*\leftarrow i}^g(H)$):

$$S_{*\leftarrow i}^g(H) = \frac{\sum_{k=1, k \neq i}^J \theta'_{ki}(H)}{\sum_{k, k \neq i}^J \theta'_{ki}(H)} * 100 = \sum_{k=1, k \neq i}^J \theta'_{ki}(H) * 100 \quad (6)$$

The third relevant measure is the NET spillover index (Eq. 7), which calculates the difference between the gross transmitted (TO) and received (FROM) shocks from all other time series:

$$S_i^g(H) = S_{*\leftarrow i}^g(H) - S_{i\leftarrow*}^g(H) \quad (7)$$

Finally, at the macro level of the network analysis, the system-wide spillover index (SUM spillover index $S_{sum}^g(H)$) offers information about the average influence one time series has on all other time series, regardless of the direction, in the following way:

$$S_{sum}^g(H) = \frac{\sum_{i, k=1, i \neq k}^J \theta'_{ik}(H)}{J} * 100 \quad (8)$$

In summary, the total spillover index is the sum of all the off-diagonal elements of the generalized FEVD matrix relative to the number of time series considered in the VAR(p) model. It summarises the measurement of how much of the FEV of the time series can be explained by spillovers from other time series. A large (small) total spillover index means that the average propagation of a shock in one time series to all others in the system is high (low) and, thus, the systemic risk of the network is high (low) (Diebold and Yilmaz, 2014).

We can further decompose the directional spillovers between two time series into net pairwise directional spillovers. This decomposition allows the spillover linkages between two specified time series to be determined. NET pairwise spillover index (NETP) between time series Y_i and Y_j is the difference between the gross

shocks transmitted from Y_i to Y_j and those transmitted from Y_j to Y_i , calculated in the following way:

$$S_{ij}^g(H) = \left(\frac{\theta_{ji}^g(H)}{\sum_{i,k=1}^J \theta_{ik}^g(H)} - \frac{\theta_{ij}^g(H)}{\sum_{i,k=1}^J \theta_{ik}^g(H)} \right) * 100 \quad (9)$$

As Diebold and Yilmaz (2014) pointed out, having a positive (negative) value of the net pairwise directional spillovers implies that time series Y_j dominates (is dominated by) time series Y_i .

During turbulent periods, an increase in the average pairwise spillovers (NETP) from one time-period to another corresponds to an increase in the total spillover index (SUM) of the system. In the DY empirical literature, abrupt increases in total spillover index or pairwise spillover indices are often interpreted in relation to systemic shocks (Diebold and Yilmaz, 2014; Greenwood-Nimmo and Tarassow, 2022). Following Diebold and Yilmaz (2012; 2014), almost all the researchers apply a rolling window approach, because it is a simple and effective way to analyse the dynamics of the linkages between the network of time series.

In order to create a full comparison between the indicators, in my empirical analysis I use both macro (SUM) and aggregated micro (NET) spillover indices, both in a static and a dynamic way to analyse the linkages between the financial institutions. The block-aggregation method of Greenwood-Nimmo et al. (2016) is a flexible tool to extend the spillover measures from variable to any group-level aggregation.

3 DATA

The data cover January 4 2021, to December 30 2022, with 521 daily observations. The institutions are listed in Table 1. We divide the financial institutions into three subgroups: big financial institutions (Big FI), medium banks (Medium FI), and financial institutions from the CEE region (CEE FI). My main objective is to study the spillover channels between the biggest financial institutions in Western Europe and the CEE region.

I investigate the spillovers between 10 Western European financial institutions from the UK (HSBC Holdings, Barclays), France (BNP, Credit Agricole), Switzerland (UBS), Spain (Banco Santander), Netherlands (ING Group), Italy (Intesa San Paolo, UniCredit) and Belgium (KBC Group). Besides that I analyse the role of the CEE region's biggest financial institutions (Komerční banka – CZ, OTP Bank – HUN, Bank Handlowy w Warszawie – POL and BRD Groupe Société Générale – ROM) in the banking network.

Table 1**Financial institutions, tickers and market caps at the end of 2021 in billion €.**

Panel A: Big Financial Institutions	Bloomberg Ticker	Market Cap
HSBC Holdings	HSBA	107.44
BNP Paribas	BNP	74.78
UBS	UBSG	54.67
Banco Santander	SAN	50.20
ING Group	INGA	46.23
Panel B: Medium Financial Institutions	Bloomberg Ticker	Market Cap
Credit Agricole	ACA	38.88
Intesa San Paolo	ISP	44.09
Barclays	BARC	37.23
KBC Group	KBC	31.44
UniCredit	UCG	30.15
Panel C: CEE Region Financial Institutions	Bloomberg Ticker	Market Cap
Komerčni banka	KOMB	
OTP Bank	OTP	
Bank Handlowy w Warszawie	BHW	
BRD Groupe Societe Générale	BRD	

Source: <https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/top-20-european-banks-by-market-cap-q4-21-68258343>

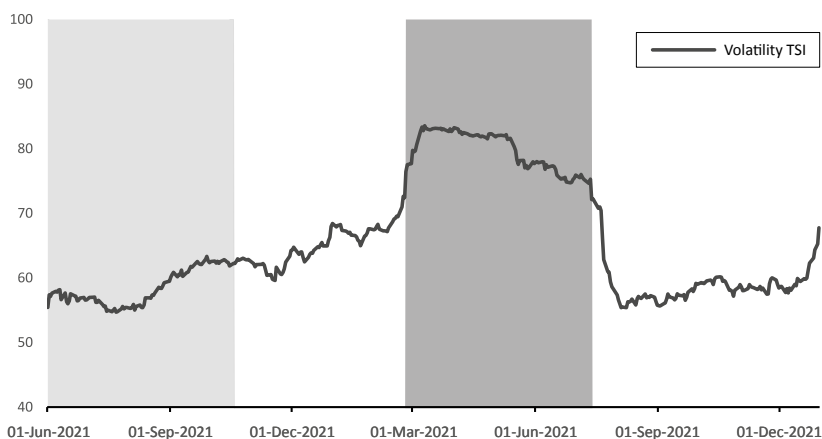
The dataset consists of daily low and high prices, extracted from Bloomberg in order to measure *Parkinson* volatility following the method of Diebold and Yilmaz (2012). I set $H = 10$ (forecast horizon) for the DY framework and $p = 1$ lag in the VAR model estimation. I use 100-day rolling window for the time-varying connectedness. These are the most commonly used parameters in the empirical literature (Diebold and Yilmaz, 2014). To strengthen my results, I also analyse the robustness of these parameters.

In the next subsection, I apply the previously introduced DY framework to perform a crisis analysis of the Russo-Ukrainian War. Using a block-aggregation method, I examine how the CEE region's volatility connections act as contagion channels during this period. Finally, I analyse the robustness of the results for the chosen DY framework parameters (window size, VAR lag).

4 EMPIRICAL RESULTS

Firstly I perform a rolling-window (dynamic) analysis on the volatility network to investigate the dynamics of the total spillover index. *Figure 1* represents the result with a 100-period rolling window, $H = 10$ forecast horizon, and $p = 1$ lags. The light grey shaded area represents a calm period in the second half of 2021, and the dark grey shaded represents the first 100 days of the Russo-Ukrainian War.

Figure 1
Volatility total spillover index for the network
from 2021-06-01 to 2022-12-30.



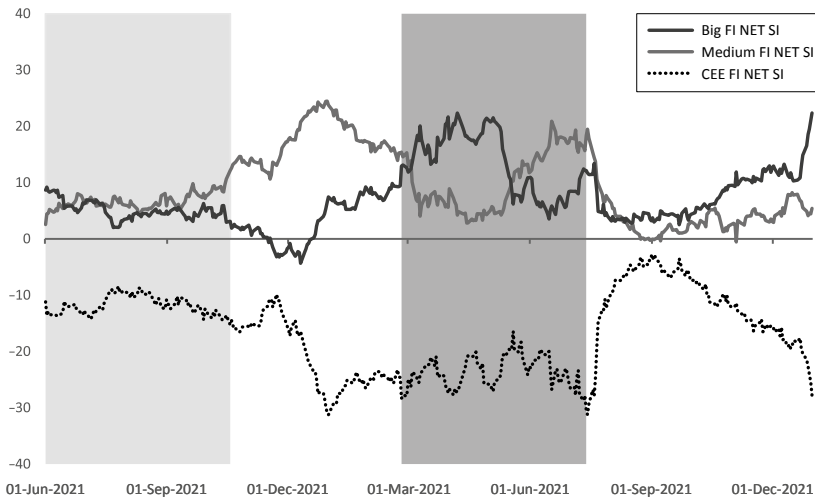
Note: The information in the Diebold-Yilmaz network is calculated from a rolling window analysis with $T = 100$, VAR(1) estimation. Dates correspond to the end date of the windows. Vertical light gray (dark gray) shaded are highlighted calm(crisis) periods.

Generally, the volatility total spillover index (TSI) ranges from 55 to 65%. However, in the middle of the examined period, the TSI index peaks almost immediately after the Russian invasion of Ukraine (2022-02-24). This peak is sustained in the first 100 days of the war after the total spillover index sharply declines to the original level of the index. Based on *Figure 1*, I can conclude the following: if a shock greater than a certain threshold hits the financial network, it becomes overheated, and strong connections appear in the system temporarily. *Figure 1* shows evidence of a structural change in the banking network during the Russo-Ukrainian War. These results align with the earlier network-based empirical literature on the financial markets and strengthens the results of Shahzad et al. (2019).

To better understand the network, I aggregate the spillover table within and between the groups (Big FI, Medium FI, CEE FI), and calculate the aggregated net spillover indices using a rolling-sample analysis. *Figure 2.* represents the result with a 100-period rolling window, $H = 10$ forecast horizon, and $p = 1$ lags. The light grey shaded area represents a calm period in the second half of 2021, and the dark grey shaded area represents the first 100 days of the Russo-Ukrainian War. Solid, dashed, and dotted lines illustrate the group-aggregated net spillover indices of the Big, medium, and CEE region financial institutions.

In general, the net spillover index for the Big and Medium groups is positive, meaning they are the network's risk transmitter⁵ participants, and the financial institutions of the CEE group play a shock receiver role (the CEE NET index is always negative). However, the indices vary during the examined period. The net spillover index for the CEE region has the largest volatility, but we can find abrupt changes in the other two net spillover indexes, mostly in turbulent times. These results supports the findings of Borri and Di Giorgio (2021).

Figure 2
Volatility group-aggregated net spillover index for the network
from 2021-06-01 to 2022-12-30.



Note: The information in the Diebold-Yilmaz network is calculated from a rolling window analysis with $T = 100$, VAR(1) estimation. Dates correspond to the end date of the windows. Vertical light gray (dark gray) shaded are highlighted calm(crisis) periods.

⁵ risk transmitter: NET value is positive

To compare a calm period before the invasion and the first four months of the war, I calculate the aggregated spillover table for two 100-day time periods (between 2021-01-04 and 2021-05-21 for the calm period and between 2022-02-24 and 2022-07-13 for the war). *Table 2* and *Table 3* show the results; information for both tables is calculated from a VAR(1) estimation.

Table 2

Group aggregated spillover table with FROM, TO and NET spillover indices for the network from 2021-01-04 to 2021-05-21

	Big FI	Medium FI	CEE FI	FROM
Big FI	57.86	38.99	3.16	42.14
Medium FI	38.18	57.77	4.05	42.23
CEE FI	10.40	11.66	77.94	22.06
TO	48.58	50.65	7.2	106.43
NET	6.43	8.42	-14.85	0

Note: The information for the Diebold-Yilmaz network is calculated from a $T = 100$, VAR(1) estimation.

Table 2 and *Table 3* strengthen the results of *Figure 2*. After the Russian invasion on 2022-02-24, the network changed; not only on the macro level but also in the deeper structure. All the net spillover indices increased in absolute terms, and the financial institutions in the CEE region play the key role - as risk receivers⁶ - in the network. This information can be important for regulators, who are monitoring the financial system on a daily basis.

Table 3

Group aggregated spillover table with FROM, TO and NET spillover indices for the network from 2022-02-24 to 2022-07-13

	Big FI	Medium FI	CEE FI	FROM
Big FI	54.03	37.02	8.95	45.97
Medium FI	39.03	51.11	9.86	48.89
CEE FI	25.25	23.99	50.76	49.24
TO	64.28	61.01	18.81	144.10
NET	18.31	12.11	-30.43	0

Note: The information for the Diebold-Yilmaz network is calculated from a $T = 100$, VAR(1) estimation.

⁶ risk receiver: NET value is negative

To check the sensitivity of the results to the window size, I calculate the financial network with 50-day and 200-day windows as well as the selected calm and war periods. *Table 4* shows that volatility connectedness results are not sensitive to window size.

Table 4
Robustness check of the group aggregated net spillover indices
with 50-day, 100-day and 200-day windows

Calm period					
First Day	Last Day	Window size	Big FI NET	Medium FI NET	CEE FI NET
2021-01-04	2021-03-12	50	5.96	10.73	-16.7
2021-01-04	2021-05-21	100	6.43	8.42	-14.85
2021-01-04	2021-10-08	200	10.31	4.43	-14.74
Russo-Ukrainian war					
First Day	Last Day	Window size	Big FI NET	Medium FI NET	CEE FI NET
2022-02-24	2022-05-04	50	24.68	12.02	-36.7
2022-02-24	2022-07-13	100	18.31	12.11	-30.43
2022-02-24	2022-11-30	200	10.74	13.18	-23.92

Note: The information for the Diebold-Yilmaz network is calculated from a $T = 100$, VAR(1) estimation.

Besides that, to check the sensitivity of the results to the lag selection of the VAR(p) model, I calculate the financial network with a VAR(2) model as well. *Table 5* shows that volatility-connectedness results are not sensitive to the VAR(p) model lag parameter.

Table 5
Robustness check of the group aggregated net spillover indices with VAR(1) and VAR(2) models

Calm period					
First Day	Last Day	VAR lag	Big FI NET	Medium FI NET	CEE FI NET
2021-01-04	2021-05-21	1	6.43	8.42	-14.85
2021-01-04	2021-05-21	2	5.57	8.12	-13.69
Russo-Ukrainian war					
First Day	Last Day	VAR lag	Big FI NET	Medium FI NET	CEE FI NET
2022-02-24	2022-07-13	1	18.31	12.11	-30.43
2022-02-24	2022-07-13	2	16.32	11.17	27.49

Note: The information for the Diebold-Yilmaz networks is calculated from a 100-day window.

At the end of this section, I conclude that the extended Diebold-Yilmaz framework is a robust, powerful tool for undertaking crisis analysis and can identify the key groups of financial institutions and contagion channels. Similar to the earlier empirical literature, large banks play a critical role in volatility risk transmission in calm periods in my analysis. I complete this with a new finding, because financial institutions from the CEE region were the key participants in the network during the first 100 days of the Russo-Ukrainian war.

Despite the several advantages of the original Diebold-Yilmaz framework (Diebold and Yilmaz, 2014), it has a shortcoming, too. The approach only captures the linear relationship between the time series due to the VAR model concept. If researchers assume nonlinear linkages between the financial institutions, they can apply the TVP-VAR version of the framework (Antonakakis et al., 2020), which handles nonlinear relations using time-varying parameter estimation.

My results are relevant for regulators as they provide insights into the behaviour of the European banking network during turbulent and tranquil periods. My findings related to the financial institutions from the CEE region during crisis periods can be important for identifying European SIFIs.

5 CONCLUSION

This paper examined dynamic and static volatility spillover between 14 European banks over the last two years, focusing on the Russo-Ukrainian war. For this purpose, I applied a network-based analysis. To analyse the role of the smaller financial institutions in the network, I included four banks from the CEE region. My results provide an essential insight into the structure of the European banking system during calm and turbulent periods. Both the static and dynamic analyses highlight that the network is highly interconnected. I find that the volatility connectedness of the system reaches its maximum at the time of war. In my examined period, big and medium financial institutions from Western Europe play a shock transmitter role, while CEE region banks play a receiver role. These institutions were the key participants in the network during the first 100 days of the Russo-Ukrainian war, as the net spillover index decreased during this period. The study on the impact of the Russo-Ukrainian war on the banking network is still at an early stage. My results suggest considering the banking network's micro and group-aggregated level volatility connectedness in building an early-warning system to detect troubled financial institutions.

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