ISSN 1611-1699 / eISSN 2029-4433

VILNIUS TECH
Vilnius Gediminas Technical University

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2025
Volume 26
Issue 6
Pages 1358–1385
https://doi.org/10.3846/jbem.2025.25349

EAST-WEST RISK CONNECTEDNESS IN THE EUROPEAN BANKING SECTOR

András BETHLENDI ✉, Miléna Dóra SZABÓ

Department of Finance, Faculty of Economic and Social Sciences (GTK), Budapest University of Technology and Economics (BME), Budapest, Hungary

Article History:
- received 27 March 2025
- accepted 31 October 2025

Abstract. This study examines the risk spillover dynamics between banks in Central and Eastern Europe (CEE) and Western Europe (WE) across 30 banking groups from 2014 to 2023, segmented into three distinct periods: pre-COVID-19, during COVID-19, and the Russo-Ukrainian conflict. The key contribution of the paper lies in combining a cross-regional perspective with a longer time horizon, covering major shocks. Utilizing the Diebold-Yilmaz interconnectedness index model, we analyze volatilities derived from daily stock prices to identify key players in the transmission and absorption of financial shocks. Our findings, supported by existing literature, reveal a strong interconnectedness between the two parts of Europe. WE banks are more likely to be shock transmitters, while CEE banks play the role of shock receivers. However, during the Russo-Ukrainian war, CEE banks appeared more among the net transmitting banks. Although one of the main features of the CEE financial system is its dependence on WE, a bank nationalism has also emerged in some countries. This may nuance the dynamics of CEE financial stability: reducing the magnitude of WE shock, but in the case of CEE-specific shocks, the possibility of risk transfer (dispersion) is also weakened.

Keywords: volatility spillover, systemic risk connectedness, Central and Eastern Europe, COVID-19, Russo-Ukrainian war, banking.

JEL Classification: G01, G21, C32.

✉Corresponding author. E-mail: ***bethlendi.andras@gtk.bme.hu***

1. Introduction

In this paper, we examine the spillover effects of banking system risks across 30 banking groups in Central and Eastern Europe (CEE) and Western Europe (WE) from January 2014 to December 2023. Our analysis is based on the Diebold-Yilmaz Volatility Spillover Index model, applied to the volatilities calculated from the daily closing stock prices of 30 banking groups. This calculation provides a clear picture of the risk spillovers among institutions.

Volatility spillover effects are a crucial phenomenon in financial markets, indicating the interdependence among different systems and signifying that volatility in one financial market can impact another. This phenomenon intensifies during financial crises or various shocks, as the fear of contagion can rapidly spread uncertainty from one institution or market to another, increasing the instability and risk of the entire financial system (Diebold & Yilmaz, 2009, 2016; Ghulam & Doering, 2018; Gunay, 2020; Onwumere et al., 2018).

Risk transmission is a process that demonstrates the spread of financial shocks and risks from one market to another. Its magnitude and direction depend on various factors, including market relationships, liquidity conditions, and interactions among financial institutions. In the literature, this is also referred to as the contagion effect, where economic problems in one institution or country rapidly spread to others.

Understanding risk transmission and contagion effects is essential for maintaining financial stability, as these phenomena increase systemic risk and can threaten the stability of the financial system in the long term (Cerqueti et al., 2024; Paltalidis et al., 2015; Wang et al., 2022). Advanced risk analysis methods and cross-border supervisory systems can significantly enhance the resilience of the financial system (Glasserman & Young, 2016; Prorokowski, 2013).

One of the main features of the economic and financial system of the CEE region is its dependence on the West. The CEE financial sector is characterized by a high foreign ownership ratio. The freedom of capital flows and cross-border services have significantly reduced the ability of CEE countries to control their financial markets and have increased financial stability and contagion risks (Piroska et al., 2021).

Following the 2008 crisis, the phenomenon of so-called "bank nationalism", i.e., the policy of increasing domestic ownership in the banking system, intensified in the region. (Mérő & Piroska, 2016) In parallel, a complex system of macroprudential supervision tools was created in the European Union. In this new supervision framework, Piroska et al. (2021) showed that dependent CEE countries use macroprudential tools differently, in many cases supporting their bank nationalist policies. Thus, we consider it a relevant research question whether this bank nationalism has affected the direction and intensity of contagions.

In our study, we examine the following three hypotheses.

H.1. There is a strong risk (volatility) interconnectedness between WE and CEE banking groups. This hypothesis is grounded in the existing literature. For example, Paltalidis et al. (2015) found very strong relationships among members of the EU banking system. We expect the same between WE and CEE banking groups.

H.2. WE banks are more likely to be shock net transmitters (give more risk to others than receive), while CEE banks play the role of shock net receivers (receive more risk than give to others). This hypothesis is based on the theory of dependent financialization and the empirical evidence. According to Shahzad et al. (2019), larger banks are typically transmitters of shocks, while smaller banks are receivers in the EU. CEE banks are typically much smaller than their Western peers.

However, the typical relationship assumed above might change over time and depending on the type of shock. Particularly, the Russo-Ukrainian war may have altered the direction of risk transmission.

H.3. Specific shock (e.g. Russo-Ukrainian war) could alter the general geographical direction of risk transmission. In such period CEE banks would appear more among the net transmitting banks.

The structure of our study is as follows. Section 2 provides an overview of the relevant literature. Section 3 describes the methodological approach and its main steps. Section 4 introduces the selected banking groups and data. Section 5 presents descriptive statistics and model results. It is followed in Section 6 by the discussion and interpretation of the results obtained. Finally, the Conclusion section summarizes the main findings of our research and discusses our contribution to the literature.

2. Literature review

A variety of methodological approaches have been developed to analyze volatility spillovers, each offering different insights into volatility transmission mechanisms and risk dynamics across financial systems. In this study, we apply the Diebold-Yilmaz model, as it best fits our research objectives. Below, we review the most commonly used alternative approaches and provide a justification for our methodological choice.

CDS spread analysis examines the direction and magnitude of risk transmission from one organization to another. It defines contagion as excess correlation that cannot be explained by fundamental factors. For example, Dreassi et al. (2018) used linear factor model and excess correlation approach to point out the main factors that play key roles in risk transmission among banks and insurance companies.

The cross-quantile approach provides a methodological framework for measuring spillover effects among financial markets. By examining the distribution of returns, it considers that different relationships may emerge in different quantiles. This approach allows for a more precise examination of dynamic relationships and market interdependencies, making the spread of shocks under different market conditions more understandable. For instance, in a bear market, the financial sector may have a stronger impact on banks, while in a bull market, banks may exert more influence on the financial sector (Shahzad et al., 2019).

Foglia and Angelini (2020) applied the Tail-Event driven NETwork (TENET) method to study risk transmission among eurozone financial institutions. The method is based on the CoVaR framework and consists of three main steps. First, it calculates the risk level of financial institutions and the risk transmission between them using Value at Risk (VaR) and Conditional Value at Risk (CoVaR) indicators. Second, it considers the high-dimensional environment, applies nonlinear regression, and introduces two new risk indicators: Systemic Risk Receiver (SRR) and Systemic Risk Emitter (SRE) indices. Finally, it visualizes the relationships among financial institutions using network analysis and determines the risk contribution of different sectors (Foglia & Angelini, 2020).

Wavelet coherence analysis is another technique often used to examine time- and frequency-dependent co-movements between financial variables. It is suitable for smooth, macro-level series such as bond yields or interbank rates, and has been applied to detect dynamic integration patterns across markets (Vukovic et al., 2021). However, wavelet coherence does not provide directional or net spillover measures, and is less applicable to high-frequency, bank-level volatility data with structural breaks. In addition, it is typically applied in pairwise settings (e.g., two time series at a time). Among the methods, the most widely used is the Diebold and Yilmaz (2012, 2014) model, which we also employ to measure the extent of spillover effects. Their method is a generalized vector autoregressive (VAR) framework for measuring volatility spillover. It uses the decomposition of forecast error variance, which is invariant to the order of variables. This method allows for the examination of both directed and total spillovers, precisely determining the extent to which the volatility of one market affects others and vice versa.

Table 1 illustrates the wide variety of methodological approaches and empirical contexts in which volatility spillover has been analyzed.

Several empirical studies have examined volatility spillovers in European banking systems. Though cross-regional analyses between WE and CEE banks is scarce. Only Badics (2023) investigated this research question. He found that CEE banks typically act as net receivers of volatility, while WE banks act as net transmitters. His analysis also demonstrates that these roles can shift under major geopolitical shocks, as CEE banks gained central importance in the network during the early phase of the Russo-Ukrainian war. This is broadly consistent with the pattern observed by Maurya et al. (2024), who report that developed markets act as net transmitters of volatility toward developing ones, although their study does not specifically address CEE banking systems. However, Badics' study was based on a relatively small sample of fourteen banks, with only four CEE banks analyzed as a single group, which limits the granularity of the findings regarding the CEE region.

Table 1. Relevant literature

Article	Data		Area	Method
	Time	Investigated type of institution/market		
Albrecht and Kočenda (2024)	2009–2022	Foreign exchange market	CEE	Diebold-Yilmaz
Alemany et al. (2015)	2006–2013	CDS market	Eurozone and non-eurozone	Asymmetric multivariate Baba-Engle-Kraft-Kroner model
Andries and Galasan (2020)	2006–2016	Commercial banks	EU-27	SDSVaR
Badics (2023)	2021–2022	Commercial banks	CEE and WE	Diebold-Yilmaz
Baruník et al. (2017)	2007–2015	Foreign exchange market	Global	Diebold-Yilmaz
Boţoc and Anton (2020)	2000–2016	Stock market	CEE	PCA
Cerqueti et al. (2024)	2021	Same bank customers	Italy	complex network
Christiansen (2007)	2001–2017	Government bond market	Western and Northern Europe	GARCH
Demirer et al. (2018)	2003–2014	Top 150 banks	Global	LASSO and Diebold-Yilmaz
Demirer et al. (2019)	1963–2016	Stock market	USA	Diebold-Yilmaz
Dreassi et al. (2018)	2006–2014	Banks and insurance companies	WE	Linear factor model and excess correlation approach
Foglia et al. (2022)	2005–2020	Commercial banks	Eurozone	Diebold-Yilmaz
Foglia and Angelini (2020)	2005–2017	Banks, insurance companies, and shadow banking system	Eurozone	TENET
Ghulam and Doering (2018)	2003–2015	Banks, insurance companies, investment funds	Germany and UK	SDSVaR and quantile regression
Hautsch et al. (2015)	2000–2008	Financial institutions	USA	Network-based systemic risk and LASSO
Kang and Lee (2019)	2002–2018	Futures market	Global	Diebold-Yilmaz

End of Table 1

Article	Data		Area	Method
	Time	Investigated type of institution/market		
Karimalis and Nomikos (2017)	2002–2012	Large European banks	Europe	CoVaR
Karkowska and Urjasz (2021)	2008–2020	Government bond market	CEE	Diebold-Yilmaz
King et al. (1994)	1970–1988	Stock market	Global	Multivariate factor model
Maghyereh et al. (2016)	2008–2015	Crude oil and stock markets	Global	Diebold-Yilmaz
Maurya et al. (2024)	2014–2023	Stock market	G20	Diebold-Yilmaz
Nerantzidis et al. (2024)	2016–2022	Main European currencies	Europe	QVAR
Paltalidis et al. (2015)	2005–2013	Commercial banks	Eurozone	maximum entropy method
Pan and Sun (2023)	2018–2023	Crude oil and futures markets	Global	GJR-GARCH
Shahzad et al. (2018)	2001–2016	Stock market	Global	bivariate cross-quantilogram
Shahzad et al. (2019)	2001–2017	Banks and financial sector	Europe	cross quantile
Vidal-Llana et al. (2023)	2015–2021	Stock market	EU-27	Diebold-Yilmaz
Wang et al. (2022)	2014–2019	Commercial banks	Belt Road countries	TENET
Wang et al. (2018)	2008–2016	Commercial banks	China	Diebold-Yilmaz
Yilmaz (2010)	1992–2009	Stock market	East-Asia	Diebold-Yilmaz

Moreover, most of the literature has focused on spillover patterns during specific crisis episodes, leaving the evolution of risk transmission across different market environments relatively underexplored. One of the exceptions is Yilmaz (2010), who found that volatility spillovers in East Asian stock markets exhibit different behaviors during crisis and non-crisis periods, suggesting that market conditions can influence the magnitude and direction of these spillovers.

In response to these gaps, this study conducts a bank-level analysis of volatility spillovers between CEE and WE banks over different sub-periods between 2014 and 2023.

Understanding volatility spillovers also requires a theoretical perspective on systemic risk and financial contagion. Karimalis and Nomikos (2017) point out, systemic risk reflects the potential for financial distress at one institution to spread throughout the financial system due to institutional interconnectedness and common market exposures.

Network-based contagion models show that both direct financial exposures and indirect channels (such as structural interdependencies) can facilitate the spread of risks, particularly during periods of market stress (Chen et al., 2020). In this context, risk contagion driven by asymmetric information and amplified by market sentiment can magnify perceived risks beyond fundamental values and accelerate spillover effects (Chen et al., 2022).

Banks play a central role in volatility transmission across financial systems, as highlighted in numerous studies examining systemic risk and financial contagion. The concept of systemic risk and related macroprudential tools were introduced into banking regulation and supervision only after the global financial crisis (Basel III rules). According to Gropp and Moerman (2004), difficulties in one banking system can spread to another country's banking system. Furthermore, Billio et al. (2012) found that among four categories of financial institutions (banks, insurers, hedge funds, and brokers), banks are the primary transmitters of shocks. Based on these findings, we can conclude that banks play a crucial role in spillover effects. Regulatory frameworks and macroprudential policy interventions substantially influence the extent to which systemic risks materialize and spread within the financial network (Eder & Keiler, 2015).

Paltalidis et al. (2015) concluded that there are very strong relationships among members of the European banking system. Spatial and structural asymmetries in European banking systems shape the transmission of financial risks by reinforcing the effects of regional economic disparities and structural dependencies, increasing the vulnerability of peripheral markets to externally originated shocks These findings suggest that within the European banking network, structurally stronger and more connected institutions (typically large WE banks) are more likely to act as transmitters of systemic risk, reinforcing our expectation that CEE banks primarily function as receivers of volatility. Shahzad et al. (2019) identified the roles of smaller and larger banks in the network, observing that larger banks are typically transmitters of shocks, while smaller banks are receivers. This empirical evidence further supports our hypothesis that WE banks, which are typically larger and more systemically connected, act as net transmitters of risk to smaller and more vulnerable CEE banks.

The CEE banking systems are typically bank-based financial systems. Non-financial corporations primarily rely on bank funding; capital market financing is more underdeveloped. Before the financial crisis, the dominant part of CEE banking systems was foreign-owned. Some eurozone banking groups established extensive subsidiary networks in the region. After the crisis, Poland and Hungary increased the share of domestic ownership in the banking sector (Mérő & Bethlendi, 2022). Gabor (2018) refers to emerging markets as dependent financialization, as transnational financial institutions dominate the financial markets and real economy financing in emerging economies. She argues that transnational financial corporations have transformed various aspects of financial markets and made them dependent in the sense that global financial forces have a greater influence on financial markets than local political decision-makers.

Based on this dependent relationship, it is reasonable to expect that WE banks, which dominate the financial and ownership structures in the region, act as net transmitters of risk to CEE banks, which in turn function as net receivers of volatility due to their structural dependence.

In summary, the banking systems of WE and CEE are closely interconnected. CEE banking systems have subordinate and dependent characteristics to their WE counterparts. Based on prior studies we can suppose that WE banks tend to act as net transmitters of risk and CEE banks as receivers; it remains unclear how these relationships evolve over time and in response to major shocks, such as the Russo-Ukrainian war. Moreover, existing analyses, such as Badics (2023), have focused on limited time periods and small samples, treating CEE banks as a single aggregated group. In response to these gaps, we conduct a more detailed analysis using a sample of 30 major banking groups from the WE and CEE regions, covering the period from 2014 to 2023 and applying the Diebold-Yilmaz model. By identifying the individual banks that play key roles in risk transmission and examining how these dynamics change across different market environments, this study contributes novel insights to the literature by providing a bank-level analysis of volatility spillovers between CEE and WE banks across three periods (pre-Covid, Covid, and war), a perspective that has not been addressed in prior research, thereby filling an important gap in the literature on cross-regional bank-level risk transmission dynamics in Europe.

3. Methodology

3.1. Volatility measurement and model setup

Before applying the model, we briefly discuss the main reasons why the Diebold-Yilmaz framework is appropriate for this cross-regional, bank-level analysis. The framework is particularly suitable for this research for several reasons. First, it requires relatively limited data inputs: only time series of daily closing stock prices, which are available for the selected sample of banks across both regions, and from which returns or volatility proxies can be derived. This is advantageous in a cross-regional context like ours, where detailed and comparable micro-level data on interbank exposures or CDS spreads are largely unavailable, especially for CEE banks. Second, the DY framework is fully data-driven and model-free in terms of requiring no assumptions about the underlying structural relationships between institutions. Third, its variance decomposition approach naturally supports aggregation across groups of banks and comparison of directional effects, allowing us to analyze systemic risk dynamics both at the individual bank level and in cross-regional terms. These features make the DY model well-suited to studying volatility spillovers between CEE and WE banks over an extended period and across different market phases. Moreover, the DY framework is widely used in the existing literature, making our results easily comparable to those of previous studies on volatility spillovers.

To apply the DY framework, we first compute the volatility series to be used as input in the model. Forsberg and Ghysels (2007) demonstrated that absolute returns effectively predict volatility. Therefore, absolute returns are commonly used in the relevant literature instead of volatility for calculations. Forsberg and Ghysels (2007) further emphasize that absolute returns are not only empirically efficient but also theoretically sound proxies for volatility. Unlike squared returns, they are less sensitive to extreme outliers and better capture the persistent, long-memory nature of market fluctuations.

Following the formula (Eq. (1)) used by Antonakakis and Kizys (2015), Antonakakis et al. (2018), Gong et al. (2021), and Foglia et al. (2022), we calculate the volatilities. Here, $p_{i,t}$ represents the daily (t) closing stock prices (p) for each bank (i). In the following sections, whenever we refer to volatility, we mean this logarithmic absolute return:

$$V = \left| \ln p_{i,t} - \ln p_{i,t-1} \right|. \tag{1}$$

Our data must be statistically analyzed to determine which banks are more sensitive to various shocks, providing an initial understanding of their potential roles in the system. Additionally, it is crucial to use statistical tests to determine whether our data follows a normal distribution and to ensure that the stationarity requirement for the Vector Autoregressive (VAR) model is met for subsequent calculations (Foglia et al., 2022).

We apply the Diebold and Yilmaz volatility connectedness network model to examine spillover effects among 15 CEE and 15 WE banking groups, following the methodology of

Diebold and Yilmaz (2012, 2014) and Foglia et al. (2022). The method is based on the covariance stationarity VAR(p) model, as shown in Eq. (2):

$$Y_t = \sum_{i=1}^{p} \theta_i Y_{t-i} + \varepsilon_t, \tag{2}$$

where Y_t is a $N \times 1$ vector of endogenous variables at time *t*, *p* is the lag order of the VAR model, θ_i –*s* are $N \times N$ coefficient matrices, and ε_t is a $N \times 1$ vector of independent and identically distributed random variables (white noise). The stationary vector autoregressive VAR(p) model can be expressed as a moving average, as shown in Eq. (3):

$$Y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}, \tag{3}$$

where the $N \times N$ A_j –*s* are the coefficient matrices formed as shown in Eq. (4), such that A_0 is an $N \times N$ identity matrix, and $A_j = 0$, if $j < 0$.

$$A_j = \theta_1 A_{j-1} + \theta_2 A_{j-2} + \cdots + \theta_p A_{j-p}. \tag{4}$$

The variance decomposition coefficient is the basis of the model, which we calculate using the generalized variance decomposition (GVD) framework, invariant to the order of variables. Therefore, the generalized forecast error variance for an H-step-ahead forecast is given by Eq. (5):

$$\theta_{ij}^{g}(H) = \frac{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}, \tag{5}$$

where the $N \times N$ covariance matrix of the error vector ε is denoted by Σ and e_i is a selection vector of size $N \times 1$ that takes the value 1 at position i and 0 elsewhere. This results in the $N \times N$ generalized variance decomposition matrix. Here we did not apply the σ_{jj}^{-1} normalization term, as our objective was to examine the absolute level of contagion rather than its scaled (relative) form. We then divide each row by its sum, normalizing the matrix, as shown in Eq. (6), so that the sum of each row is exactly 1.

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{6}$$

Finally, using the elements of the normalized matrix, the total volatility connectedness index (*TVC*) can be defined as shown in Eq. (7):

$$TVC(H) = \frac{\sum_{ij=1,\, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{ij=1,\, i \neq j}^{N} \theta_{ij}(H)} \times 100 = \frac{\sum_{ij=1,\, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100. \tag{7}$$

3.2. Connectedness indices

Now, we can introduce three additional directional connectedness indices.

From-connectedness measures the extent to which a bank receives volatility effects from other banks, calculated as shown in Eq. (8):

$$DS_{i \leftarrow j}(H) = \frac{\sum_{j=1,\, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{ij=1,}^{N} \theta_{ij}(H)} \times 100 = \frac{\sum_{j=1,\, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 . \tag{8}$$

To-connectedness measures the extent to which a bank transmits volatility effects to other banks, calculated as shown in Eq. (9):

$$DS_{i \to j}(H) = \frac{\sum_{j=1,\, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{\sum_{ij=1}^{N} \theta_{ji}(H)} \times 100 = \frac{\sum_{j=1,\, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100 . \tag{9}$$

Net-connectedness shows the net effect, i.e., the aggregated connections between banks, which is the difference between the total transmitted and received effects.

$$NS_i(H) = DS_{i \to j}(H) - DS_{i \leftarrow j}(H) . \tag{10}$$

The net connectedness values help us to determine whether a bank is a net receiver or transmitter of volatility spillover. Together, these connectedness indices provide a comprehensive view of volatility transmission dynamics in the CEE and WE banking networks, fully aligned with the cross-regional, bank-level focus of this study.

3.3. Rolling window robustness analysis

We examine the time-varying nature of volatility connectedness using a rolling window approach, in line with Diebold and Yilmaz (2012, 2014) and Foglia et al. (2022). This VAR-based framework allows us to dynamically re-estimate the connectedness matrix over moving windows, enabling us to trace the evolution of Total Volatility Connectedness (TVC) over time. This approach captures the impact of external shocks, with crisis periods (such as COVID-19 or the Russia-Ukraine war) clearly reflected in the connectedness indices.

We conduct this dynamic analysis as part of a robustness check to evaluate whether the time-varying results are consistent with our static findings. Following the literature, we repeat the analysis using different window lengths (100, 150, and 200 days) to assess the stability and reliability of our results.

3.4. Volatility and systemic risk

Although volatility may reflect market sentiment to some extent, the Diebold and Yilmaz (2012) model captures structured volatility spillovers through directional variance decomposition. Mieg (2022) reinforces this by showing that volatility can act as a transmitter and amplifier of systemic risk, particularly in reflexive financial systems. Gupta and Mishra (2024) further highlight that volatility emerges from a combination of macroeconomic shocks, liquidity, market sentiment, and behavioral factors, without reducing it solely to perception.

Therefore, our use of volatility-based connectedness measures is theoretically and empirically justified. Moreover, our focus is not on small-scale sentiment-driven fluctuations, but on major systemic events. The empirical periods under analysis include the COVID-19 outbreak and the Russo-Ukrainian war, both of which induced substantial volatility shocks and structural changes in risk transmission patterns.

4. Data and samples

To observe the bank interconnectedness of two regions and apply the Diebold-Yilmaz model, it is essential to select the banks carefully. A crucial consideration was ensuring the availability of daily closing stock price data throughout the observed period from 2014 to 2023. We selected the 30 banking groups shown in Table 2, with the third column indicating the region to which each bank belongs (abbreviated as '.K' for CEE and .N for WE). However, for three banks, the '.N' notation is insufficient, as they operate primarily in developed European countries but also have significant CEE exposures. Therefore, for the two Italian banks, Intesa Sanpaolo and UniCredit SpA, and the Belgian bank KBC Group, we use the '.NK' notation. In principle, a more precise regional classification can be established by breaking down the exposures in the banks' balance sheets, but this requires much granular data.

The data used for the calculations are the daily closing stock prices from January 2014 to December 2023, considering only the days when data is available for all banks, totaling 2335 daily data points per bank, downloaded from Yahoo Finance. Table 2 also includes the country of the group headquarters and the size of the group (measured by total assets). It is clearly visible that there is a significant size difference between WE and CEE banks.

Table 2. Names, headquarters country, abbreviation, and total assets of the selected 30 banks (source: Yahoo Finance, Orbis database, banks'websites)

Headquarter Country	Bank Name	Abbreviation	Total Assets (billion euros)	Total Assets (billion euros)
			as of 31.12.2014	as of 31.12.2023
Austria	Erste Group Bank	EBS.K	196.3	337.16
Austria	Raiffeisen Bank International	RBI.K	121,0	198.24
Belgium	KBC Group	KBC.NK	245,0	346.92
Czech Republic	Komercni Banka	KOMB.K	34,0	61.38
France	BNP Paribas	BNP.N	2.078	2591.49
France	Société Générale	GLE.N	1.308	1554.05
France	Crédit Agricole	ACA.N	1.589	2189.40
Greece	Alpha Bank	ALPHA.K	72,9	73.66
Netherlands	ING Group	INGA.N	993	975.58
Poland	PKO Bank Polski	PKO.K	58,4	115.29
Poland	Bank Pekao	PEO.K	39.3	70.30
Poland	Bank Handlowy	BHW.K	12	16.87
Poland	Bank Millennium	MIL.K	14	28.86
Poland	Alior Bank SA	ALR.K	7	20.72

End of Table 2

Headquarter Country	Bank Name	Abbreviation	Total Assets (billion euros)	Total Assets (billion euros)
			as of 31.12.2014	as of 31.12.2023
Poland	Bank Ochrony Środowiska S.A.	BOS.K	5	5.06
Poland	ING Bank Slaski	ING.K	23	56.40
Poland	mBank	MBK.K	28	52.18
Hungary	OTP Bank	OTP.K	35	103.69
Germany	Deutsche Bank	DBK.N	1709	1312.33
Germany	Commerzbank	CBK.N	558	517.17
Norway	DNB	DNB.N	262	305.75
Italy	Intesa Sanpaolo	ISP.NK	646,0	963.57
Italy	UniCredit SpA	UCG.NK	844,0	784.97
Romania	Banca Transilvania	TLV.K	8,0	34.04
Romania	Brd – Groupe Societe Generale	BRD.K	10,0	16.87
Spain	Banco Sabadell	SAB.N	163,0	235.72
Spain	Banco Santander	SAN.N	1.266	1797.06
Spain	BBVA	BBVA.N	632,0	775.56
Spain	CaixaBank	CABK.N	339,0	607.17
Sweden	Swedbank AB	SWED.N	226,0	256.79
Total			7287	16404
Total K.			664	1191
Totla NK.			1735	2095
Total N.			4888	13118

The size difference between CEE and WE banks is significant and has not decreased despite the growth of the CEE banking sector. Our database is representative of the CEE banking sector. We compare the total assets of CEE banks in the sample with the total assets of monetary financial institutions other than central bank of eleven CEE countries. We found that the sample represented 64% of the total assets of CEE monetary financial institutions other than central bank in 2014 and 2023 as well.

There is an ongoing consolidation process (M&A activity) in the CEE banking sector, which affects the pricing of banks, but to a much lesser extent the price volatility of a given bank. An M&A has a very limited impact on several banks at once (M&A is an idiosyncratic risk). Thus, in our opinion, it has very little effect on the spillover effect between several banks and regions.

5. Results

5.1. Descriptive statistical analysis

We determine the descriptive statistical indicators for the entire period, summarized in Table A1 (in the Appendix). The average daily returns and standard deviations indicate that the Greek Alpha Bank, Polish Bank Millennium, Italian UniCredit SpA, Spanish Banco Sabadell, and German Commerzbank exhibit the highest price volatility, potentially making them the most sensitive to financial turbulence.

The skewness values in Table A2 (in the Appendix) significantly differ from zero, and the kurtosis values significantly differ from three, which are the skewness and kurtosis values of a normal distribution. This suggests that the volatility values do not follow a (Gaussian) normal distribution. The Jarque-Bera statistic confirms this, as it is significant at the 1% level for all banks, leading to the rejection of the null hypothesis of normality. The ADF test values are negative and less than the 1% critical value for all banks, indicating that the volatilities are stationary. Thus, the stationarity requirement for the VAR model is satisfied.

Figure 1 shows the changes in calculated volatility over time, revealing that different periods' events influence volatility magnitude, with peak values observed during the COVID-19 pandemic and the Russo-Ukrainian war.

5.2. Diebold-Yilmaz model calculation results

We divided the period from 2014 to 2023 into three sub-periods for more detailed analysis: the pre-COVID-19 period from 2014 to 2019, the COVID-19 period from 2020 to 2021, and the Russo-Ukrainian war period from 2022 to 2023. We examine the relationships among banks and their changes under the influence of different shocks during these periods.

We performed the calculations following the methodological steps described in Section 4. We created a Python program that reads the daily volatility data for all banks from Excel files, then constructs the VAR(p) model using the equations presented in Section 4, where the optimal system lag is chosen as $p = 1$ based on the "Schwarz's information criterion" used in the paper by Foglia et al. (2022). Based on the VAR(1) model, we created the GVD matrix,

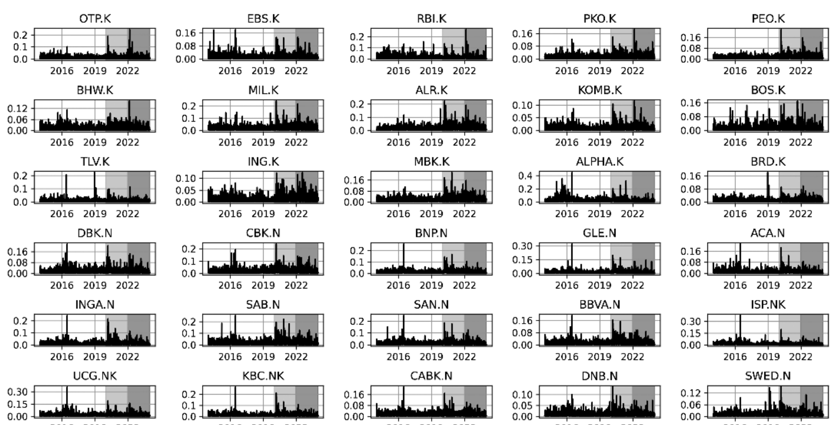

Figure 1. Changes in Bank Volatility Over the Entire Period. The lighter shading indicates the COVID-19 period, while the darker shading indicates the Russo-Ukrainian war period

normalized it, and calculated the connectedness indices. The detailed results are in Tables A3, A4, and A5 of the Appendices, which contain all the values, but we will present the most important results here.

The following subsections summarize the most important results of the from-, to-, and net-connectedness calculations at the individual bank level for each subperiod. In addition to reporting the top 10 rankings in tabular format, we interpret key patterns and highlight consistent players and shifts across time.

5.2.1. TVC results

The TVC value ranges from 0% to 100%. A value of 0% would indicate complete independence, meaning there is no relationship among the volatilities of the banks. A value of 100% would indicate complete interconnectedness, meaning that the volatility of each bank in the system fully depends on the others. Based on relevant empirical studies, the TVC value typically ranges from about 50% to 70% during calm periods but can rise above 90% in shock periods. In each period we examined, the TVC index is high, with an average of 78.32% for the entire period, confirming the strong interconnectedness among banks. Table 3 shows that the TVC index increased during the two shock periods.

Table 3. Changes in TVC index over time

Period	TVC [%]
2014–2019	67.62
2020–2021	85.59
2022–2023	82.00

5.2.2. From-Connectedness values

Table 4 shows the top 10 receiver banks for each period. In the first period (2014–2019), only WE banks appear in the ranking, indicating that these institutions were the primary recipients of volatility spillovers. In the second period (2020–2021), five CEE banks enter the top 10, which suggests a temporary shift in network positioning during the COVID-19 crisis. By the third period (2022–2023), only two CEE banks remain, indicating a partial reversion to the earlier pattern. It is also noticeable that there are significant fluctuations in the rankings. However three banks are consistently among the top 10 receivers in all periods: the French Crédit Agricole (ACA.N), the Italian Intesa Sanpaolo S.p.A. (ISP.NK), and the Norwegian DNB (DNB.N), all of which are WE banks. This consistent presence highlights their persistent role as central nodes in terms of shock absorption.

This persistent receiver role may be attributed to these banks' size, interconnectedness, and exposure to international markets, which make them more likely to absorb systemic volatility regardless of the crisis type.

Table 4. Top 10 receiver banks (Gray background indicates banks present in the top 10 for all three periods)

Rank	2014–2019	Value	2020–2021	Value	2022–2023	Value
1.	BNP.N	91.22	KOMB.K	94.19	ACA.N	93.11
2.	INGA.N	89.54	ISP.NK	93.74	BNP.N	91.95

End of Table 4

Rank	2014–2019	Value	2020–2021	Value	2022–2023	Value
3.	BBVA.N	89.49	ACA.N	92.54	ISP.NK	90.82
4.	KBC.NK	89.03	BRD.K	92.43	SAN.N	90.78
5.	SAN.N	87.94	DNB.N	92.40	INGA.N	90.21
6.	ACA.N	87.55	SWED.N	92.33	BBVA.N	89.35
7.	GLE.N	87.02	EBS.K	92.13	DNB.N	88.16
8.	CABK.N	84.54	TLV.K	91.44	KBC.NK	88.02
9.	ISP.NK	82.56	RBI.K	91.26	KOMB.K	87.81
10.	DNB.N	82.40	CABK.N	90.88	EBS.K	87.13

5.2.3. To-Connectedness values

Table 5 displays the top 10 transmitter banks across the three periods. Three WE banks are consistently in the top 10 for all periods: the French Société Générale (GLE.N), the German Commerzbank (CBK.N), and the Spanish Banco Sabadell (SAB.N). Interestingly, only two CEE banks took over the transmitter role during the COVID-19 period. However, this number increases to five in the 2022–2023 period, reflecting a significant shift. This supports our earlier hypothesis that during the Russo-Ukrainian war period, CEE banks took over the transmitter role, likely due to the region's greater involvement.

Thus, while traditional WE institutions maintained strong transmitter roles, the war period marked a notable increase in the activity of CEE banks, challenging previous assumptions of their passive systemic role.

Table 5. Top 10 transmitter banks (Gray background indicates banks present in the top 10 for all three periods)

Rank	2014–2019	Value	2020–2021	Value	2022–2023	Value
1.	UCG.NK	190.29	ALPHA.K	188.85	CBK.N	163.23
2.	ALPHA.K	183.18	GLE.N	179.76	RBI.K	155.84
3.	ISP.NK	154.24	SAB.N	135.36	DBK.N	144.46
4.	GLE.N	142.57	INGA.N	133.10	GLE.N	136.65
5.	SAN.N	114.80	BNP.N	132.81	UCG.NK	135.53
6.	DBK.N	111.36	CBK.N	129.35	MIL.K	132.71
7.	CBK.N	108.47	SAN.N	119.19	EBS.K	130.92
8.	INGA.N	102.73	BBVA.N	118.45	ALR.K	129.94
9.	SAB.N	100.99	MIL.K	114.65	PEO.K	121.21
10.	BNP.N	93.88	ACA.N	113.66	SAB.N	109.36

5.2.4. Net-Connectedness values

Net-connectedness is calculated as the difference between to-connectedness (outgoing risk) and from-connectedness (incoming risk). A positive value indicates a net transmitter role, and a negative value indicates a net receiver. Table 6 presents the top 10 net transmitters for each period. Once again, Société Générale, Commerzbank, and Banco Sabadell are among the top 10 net transmitters throughout, mirroring their positions in the to-connectedness rankings. This consistency implies that net transmission is strongly correlated with raw to-connectedness strength, which suggests that these banks not only transmit substantial risk but also receive comparatively little in return. Over time, however, several CEE banks (such as Raiffeisen Bank International (RBI.K), Erste Group Bank (EBS.K), and Bank Pekao (PEO.K)) appear as net transmitters in the 2022–2023 period. This shift confirms the increasingly active role of CEE banks in systemic risk propagation.

Table 6. Top 10 net transmitter banks for each period (Gray background indicates banks present in the top 10 for all three periods)

Rank	2014–2019	Value	2020–2021	Value	2022–2023	Value
1.	ALPHA.K	168.77	ALPHA.K	126.96	CBK.N	85.07
2.	UCG.NK	115.68	GLE.N	91.66	RBI.K	78.64
3.	ISP.NK	71.68	SAB.N	62.93	DBK.N	61.98
4.	GLE.N	55.55	INGA.N	45.22	MIL.K	58.55
5.	DBK.N	31.47	CBK.N	42.62	UCG.NK	52.09
6.	CBK.N	27.88	BNP.N	42.59	ALR.K	51.65
7.	SAN.N	26.86	MIL.K	37.64	GLE.N	50.43
8.	SAB.N	24.89	ALR.K	31.92	EBS.K	43.79
9.	INGA.N	13.19	BBVA.N	30.33	PEO.K	37.83
10.	ACA.N	4.70	SAN.N	28.82	SAB.N	29.79

Table 7 shows the top 10 net receiver banks for each period. Six banks are consistently net receivers in all periods: the Czech Komercni Banka (KOMB.K), the Swedish Swedbank AB (SWED.N), the Norwegian DNB (DNB.N), the Polish ING Bank (ING.K) and Bank Handlowy (BHW.K), and the Romanian Brd – Groupe Societe Generale (BRD.K). The first two periods are dominated by CEE banks, with 8 out of 10 top net receivers coming from the region. In contrast, during the third period, four WE banks appear among the top 10, illustrating a shift in the network structure. This change supports our hypothesis regarding the evolving geographical roles in systemic risk reception.

This pattern underscores two key conclusions: first, net-connectedness aligns with directional spillover roles (transmitter vs. receiver), second, the geographical structure of systemic vulnerability is dynamic, with WE banks not immune to becoming net receivers during region-specific crises like the Russo-Ukrainian war.

Table 7. Top 10 Net receiver banks for each period (Gray background indicates banks present in the top 10 for all three periods)

Rank	2014–2019	Value	2020–2021	Value	2022–2023	Value
1.	KOMB.K	–70.12	KOMB.K	–69.18	DNB.N	–69.17
2.	SWED.N	–59.38	BRD.K	–69.16	TLV.K	–65.12
3.	DNB.N	–58.79	BHW.K	–67.72	SWED.N	–60.50
4.	OTP.K	–56.22	TLV.K	–64.37	BRD.K	–56.55
5.	ING.K	–50.33	SWED.N	–55.20	KOMB.K	–48.74
6.	PEO.K	–43.33	OTP.K	–53.37	BHW.K	–47.22
7.	BRD.K	–37.66	ING.K	–43.78	ING.K	–40.19
8.	PKO.K	–34.54	DNB.N	–37.21	KBC.NK	–39.97
9.	BHW.K	–32.81	PKO.K	–30.00	ACA.N	–38.88
10.	EBS.K	–25.43	RBI.K	–26.00	ALPHA.K	–29.74

5.2.5. Summary comparison across periods

Comparing the three periods reveals that the interconnectedness of the banking system changed not only in intensity but also in structure. Based on the TVC index, we observe that system-wide connectedness increased significantly during times of crisis, indicating stronger and faster volatility transmission.

The to-connectedness and net transmitter values suggest that volatility spillovers tend to concentrate around a few key institutions, pointing to a certain degree of structural concentration in the system.

At the same time, shifts in systemic roles can also be observed. The from-connectedness and net receiver values show that the system's most vulnerable points are not static; they shift depending on the type and geographic origin of the shock. While WE banks were the primary recipients during the calm period, several CEE banks moved into top receiver positions during the COVID-19 period. By the time of the war, some of these CEE banks retreated, while new WE institutions emerged as major receivers.

In contrast, CEE banks progressively advanced as systemic transmitters. During the war period, not only the large WE institutions but also several smaller CEE banks became prominent transmitters of volatility, indicating a shift in their systemic importance.

5.2.6. Rolling window TVC results

Figures 2, 3, and 4 display the time evolution of the Total Volatility Connectedness (TVC) using rolling windows of 100, 150, and 200 days, respectively, over the period 2014–2023. The results are remarkably consistent across the three window sizes, which confirms the robustness of the findings. In all three figures, a significant increase in volatility connectedness can be observed around the onset of the COVID-19 pandemic and the outbreak of the Russo-Ukrainian war. Additionally, a notable spike is observed in mid-2016. While this period was not explicitly analyzed in this study, the timing suggests a potential link to the Brexit referendum, which increased the uncertainty in financial markets as well.

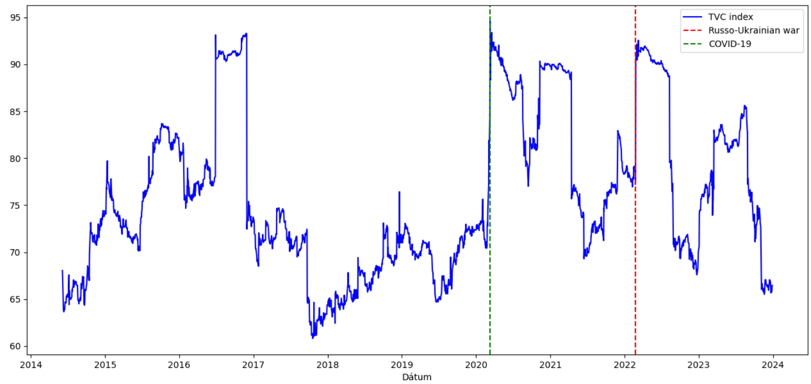

Figure 2. TVC over time using a 100-day rolling window. Major spikes appear around COVID-19, the Russo-Ukrainian war, and the Brexit referendum

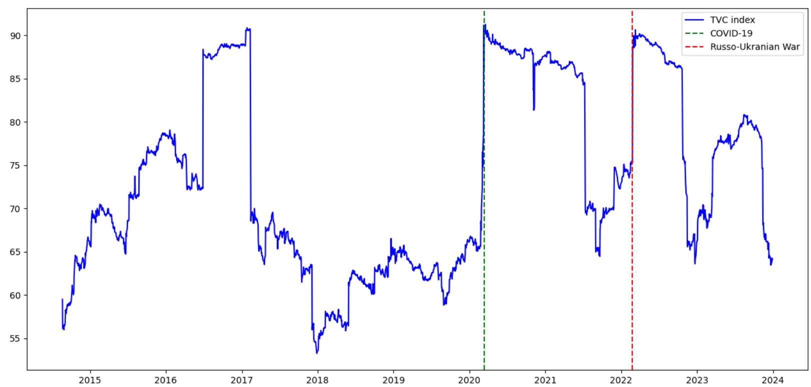

Figure 3. TVC over time using a 150-day rolling window. Similar crisis-related peaks confirm consistent dynamics

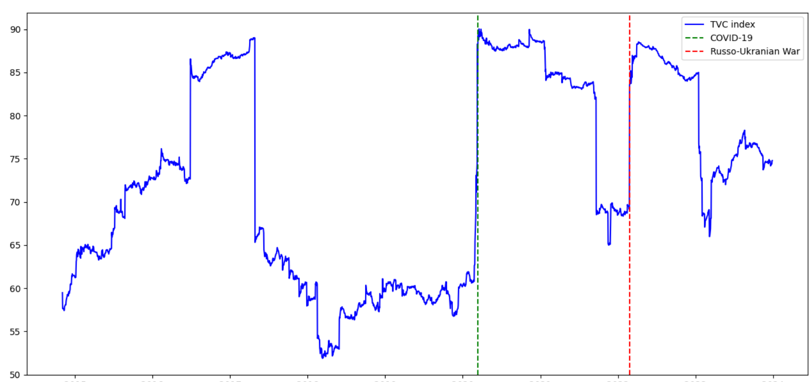

Figure 4. TVC over time using a 200-day rolling window. The stable pattern across window sizes supports robustness

Furthermore, the patterns identified in the rolling TVC results are strongly aligned with those seen in the static connectedness indices. Periods marked by elevated TVC values in the rolling analysis correspond to higher average connectedness values in the static period-based results.

To formally assess whether the differences in systemic connectedness across the three periods are statistically significant, we applied pairwise Welch's t-tests to the 100-day rolling TVC values. This method is appropriate because it does not assume equal sample sizes or variances, which fits the characteristics of our dataset.

All comparisons yielded highly significant differences in average connectedness:

- 2014–2019 vs. 2020–2021: $t = -22.84$, $df = 806.97$, $p \approx 4.20 \times 10^{-89}$
- 2020–2021 vs. 2022–2023: $t = +5.53$, $df = 910.18$, $p \approx 8.00 \times 10^{-8}$
- 2014–2019 vs. 2022–2023: $t = -14.96$, $df = 740.90$, $p \approx 4.00 \times 10^{-44}$

These results confirm that the observed increases in volatility connectedness during crisis periods are statistically highly significant. Since the static period-based TVC values are calculated from the same underlying data, this also reinforces the validity and reliability of the static findings and supports the overall robustness of the methodology.

We do not apply formal significance testing to the top 10 from-, to-, and net-connectedness rankings due to the small number of observations ($n = 10$ per period) and because these lists include only the most extreme cases by construction.

The consistency between the static and rolling window analyses confirms the robustness of the applied methodology and strengthens the reliability of the conclusions drawn.

6. Discussions

Foglia et al. (2022) examined the effects of the COVID-19 outbreak's impact on banking stability among 30 major Eurozone banks with the Diebold-Yilmaz Connectedness Index model in the period of 2005 to 2020. The results showed that the pandemic caused the total volatility connectedness (TVC) to increase from 75.8% to 90.7% and reach its maximum value at the time of the pandemic. The network structure changed significantly in the crisis.

Andries and Galasan (2020) also investigated the European banking sector, but in the pre-COVID-19 period (from 2006 to 2016), with a State-Dependent Sensitivity Value-at-Risk (SDSVaR) model. They showed that the large banks played a dominant role of contagion during the entire period, while small banks became risk transmitters mainly during times of crisis. Furthermore, the results reveal that the non-interest income of banks is the priority source of the spillover spreads.

Paltalidis et al. (2015) examined the three main channels of systemic risk (interbank lending, asset price, and sovereign credit risk) using the Maximum Entropy method. They highlighted that sovereign credit risk is the primary source of financial contagion. During a crisis, this channel infects the banking system rapidly and deeply, creating significant direct and indirect losses. Moreover, banks of the northern Eurozone proved to be more resistant against risks, while southern countries showed more vulnerability.

The study by Badics (2023) focuses on the first 100 days of the Russo-Ukrainian conflict and mainly analyzes the role of CEE banks based on the volatility network. Using the Diebold-Yilmaz framework, the author showed that the volatility connectedness of the system reached its maximum peak at the outbreak of the war. It is important to highlight that while in previous crises, mainly the WE banks took on a key role, in this case, the banks of the CEE region became the main contributors in the network.

Moreover, the results of Paltalidis et al. (2015) and Badics (2023) show that the geographical structure of systemic risk can change quickly in a drastic way, making the observation of regional network structures important.

In this paper, we examined a data series (2014–2023) including two types of shocks. We applied the Diebold-Yilmaz framework to 15 CEE and 15 WE banks. In line with previous research, we conclude that based on TVC values, the banking systems are highly interconnected, and during a crisis, even more so. The TVC grew from 67.6% in pre-COVID-19 to 85.6% during the COVID-19 pandemic, and during the Russo-Ukrainian war, it reached 82% again. We went beyond Badics' (2023) analysis by examining a longer period and a larger sample of banks and analyzing banks individually rather than in groups.

The WE and CEE banking systems are closely intertwined. In this relationship, the CEE banking systems are subordinate and, in many respects, are dependent on their WE counterparts. We have proven that despite this, shock transmission can occur in both directions. Our results proved that the dependent CEE banks took on a significant transmitter role during the Russo-Ukraine war.

Our empirical results are consistent with the three hypotheses raised in the Introduction and align well with key findings from the literature. First, the Total Volatility Connectedness (TVC) values confirmed strong systemic interconnectedness between CEE and WE banks throughout the observed periods, rising significantly during both the COVID-19 pandemic and the Russo-Ukrainian war. This supports our first hypothesis and reflects trends reported in Foglia et al. (2022) and Diebold and Yilmaz (2015), who observed similar surges in connectedness during periods of financial turbulence.

Second, our analysis showed that Western European banks generally acted as net transmitters of volatility, while CEE banks predominantly functioned as net receivers (especially in the pre-COVID and COVID-19 periods). This finding confirms our second hypothesis and aligns with prior studies (e.g., Badics, 2023; Shahzad et al., 2019) that highlight the structural role of large Western banks in volatility propagation.

Third, during the 2022–2023 Russo-Ukrainian war period, several CEE banks emerged among the top net transmitters, while certain WE banks appeared as net receivers. The mentioned CEE banks have had large direct exposures in Ukraine and Russia. However, the indirect macroeconomic effects (e.g., because of sanctions) were stronger as well in their case compared with WE counterparts. This confirms our third hypothesis and supports the argument that geopolitical proximity and regional exposure can temporarily reverse traditional risk transmission roles, an observation also made by Badics (2023), though our longer time frame and broader bank-level sample provide deeper insight.

7. Conclusions

In our study, we examined the volatility interconnectedness among 15 CEE and 15 WE banks from January 2014 to December 2023, divided into three distinct periods: the pre-COVID-19 period (2014–2019), the COVID-19 period (2020–2021), and the Russo-Ukrainian war period (2022–2023), to better understand the impact of different shock periods.

We reviewed the relevant literature on volatility spillover and found that while there is extensive research on the topic, there is limited focus on the CEE region. Badics (2023) examined a shorter period and a smaller sample of banks, while we extended the analysis with a longer period, a larger sample, and individual bank analysis.

We used daily closing stock prices to determine daily volatility levels and applied the Diebold-Yilmaz model to identify spillover effects. The model allowed us to examine banking sector interconnectedness through various measures, such as total and net directed volatility connectedness. We identified which institutions played roles as transmitters or receivers of volatility and how these roles changed over different periods.

We confirmed our first hypothesis that there is strong interconnectedness between the two regions' banks. The Total Volatility Connectedness (TVC) index is high even during calm periods and increases further during shock periods.

The results supported our second hypothesis that WE banks are generally net transmitters of shocks, while CEE banks are net receivers in line with the theory of dependent financialization.

We also confirmed our third hypothesis that during the Russo-Ukrainian war period, some CEE banks took over the role of net transmitters, while some WE banks became net receivers. The reason behind this shift may be that CEE banks have much greater direct exposure to Ukraine and Russia; in addition, the macroeconomic indirect effects on the banking sector (for example, the impact of sanctions) are also stronger.

We highlight the importance of the geographical structure of systemic risk in the European banking sector. Furthermore, we highlight that with the further spreading of bank nationalism in the region (increasing domestic ownership, funding, and discretionary macroprudential policies), the integration of CEE banking systems with the West is expected to decrease. While this may reduce the magnitude of shocks coming from the West, in the case of CEE-specific shocks, the possibility of risk transfer (dispersion) also weakens.

We draw attention to the fact that certain national-level policies and geopolitics can shape connections and spillover effects between banking systems. In addition to market processes, it is recommended to pay more attention to these changes in the future when assessing financial stability risks.

This study has some limitations. First, the absence of detailed bank-level balance sheet data – particularly concerning regional and interbank exposure breakdown – constrains our ability to fully capture the transmission and spillover effects within the financial system. Second, observed price changes may reflect not only contagion dynamics but also other factors such as market sentiment and idiosyncratic risk. However, we consider the influence of market sentiment to be limited in our context, as our analysis focuses on periods of systemic shocks, and the use of a sufficiently large sample mitigates the impact of institution-specific volatility through diversification.

Future research could explore how macroprudential tools can reduce risk interconnectedness and systemic risk at the European level. In addition, extending the analysis to non-bank financial institutions (shadow banking entities) such as money market funds, financial companies engaged in lending, and other non-bank financial institutions may offer further insights into hidden channels of cross-border volatility transmission.

Funding

The research was supported by National Research, Development and Innovation Office (Grant number: NKFIH138562).

References

Albrecht, P., & Kočenda, E. (2024). Volatility connectedness on the central European forex markets. *International Review of Financial Analysis*, *93*, Article 103179. https://doi.org/10.1016/j.irfa.2024.103179

Alemany, A., Ballester, L., & González-Urteaga, A. (2015). Volatility spillovers in the European bank CDS market. *Finance Research Letters*, *13*, 137–147. https://doi.org/10.1016/j.frl.2015.02.003

Andries, A. M., & Galasan, E. (2020). Measuring financial contagion and spillover effects with a state-dependent sensitivity value-at-risk model. *Risks*, *8*(1), Article 5. https://doi.org/10.3390/risks8010005

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., & Perez de Gracia, F. (2018). Oil volatility, oil and gas firms and portfolio diversification. *Energy Economics*, *70*, 499–515. https://doi.org/10.1016/j.eneco.2018.01.023

Antonakakis, N., & Kizys, R. (2015). Dynamic spillovers between commodity and currency markets. *International Review of Financial Analysis*, *41*, 303–319. https://doi.org/10.1016/j.irfa.2015.01.016

Badics M. C. (2023). A közép-kelet-európai régió bankszektorának szerepe az orosz–ukrán háború idején: Egy volatilitáshálózat-alapú megközelítés. *Gazdaság és Pénzügy*, *10*(4), 427–445. https://doi.org/10.33926/GP.2023.4.5

Baruník, J., Kočenda, E., & Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, *77*, 39–56. https://doi.org/10.1016/j.jimonfin.2017.06.003

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010

Boţoc, C., & Anton, S. G. (2020). New empirical evidence on CEE's stock markets integration. *The World Economy*, *43*(10), 2785–2802. https://doi.org/10.1111/twec.12961

Cerqueti, R., Pampurini, F., Quaranta, A. G., & Storani, S. (2024). Risk transmission, systemic fragility of banks' interacting customers and credit worthiness assessment. *Finance Research Letters*, *62*, Article 105061. https://doi.org/10.1016/j.frl.2024.105061

Chen, S., Guo, L., & Qiang, Q. (2022). Spatial spillovers of financial risk and their dynamic evolution: Evidence from listed financial institutions in china. *Entropy*, *24*(11), Article 1549. https://doi.org/10.3390/e24111549

Chen, T., Yang, Q., Wang, Y., & Wang, S. (2020). Double-layer network model of bank-enterprise counterparty credit risk contagion. *Complexity*, *2020*, Article 690848. https://doi.org/10.1155/2020/3690848

Christiansen, C. (2007). Volatility-spillover effects in European bond markets. *European Financial Management*, *13*(5), 923–948. https://doi.org/10.1111/j.1468-036X.2007.00403.x

Demirer, M., Diebold, F. X., Liu, L., & Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, *33*(1), 1–15. https://doi.org/10.1002/jae.2585

Demirer, M., Gokcen, U., & Yilmaz, K. (2019). *Financial sector volatility connectedness and equity returns*. SSRN. https://doi.org/10.2139/ssrn.3099738

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), Article 1. https://doi.org/10.1016/j.jeconom.2014.04.012

Diebold, F. X., & Yilmaz, K. (2016). Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004–2014. *Journal of Financial Econometrics*, *14*(1), 81–127. https://doi.org/10.1093/jjfinec/nbv021

Dreassi, A., Miani, S., Paltrinieri, A., & Sclip, A. (2018). Bank-insurance risk spillovers: Evidence from Europe. *The Geneva Papers on Risk and Insurance – Issues and Practice*, *43*(1), 72–96. https://doi.org/10.1057/s41288-017-0049-0

Eder, A., & Keiler, S. (2015). CDS spreads and contagion amongst systemically important financial institutions: A spatial econometric approach. *International Journal of Finance & Economics*, *20*(3), 291–309. https://doi.org/10.1002/ijfe.1516

Foglia, M., Addi, A., & Angelini, E. (2022). The Eurozone banking sector in the time of COVID-19: Measuring volatility connectedness. *Global Finance Journal*, *51*, Article 100677. https://doi.org/10.1016/j.gfj.2021.100677

Foglia, M., & Angelini, E. (2020). From me to you: Measuring connectedness between Eurozone financial institutions. *Research in International Business and Finance*, *54*, Article 101238. https://doi.org/10.1016/j.ribaf.2020.101238

Forsberg, L., & Ghysels, E. (2007). Why do absolute returns predict volatility so well? *Journal of Financial Econometrics*, *5*(1), Article 1. https://doi.org/10.1093/jjfinec/nbl010

Gabor, D. (2018). *Understanding the financialisation of international development through 11 FAQs*. Heinrich Böll Stiftung North America.

Ghulam, Y., & Doering, J. (2018). Spillover effects among financial institutions within Germany and the United Kingdom. *Research in International Business and Finance*, *44*, 49–63. https://doi.org/10.1016/j.ribaf.2017.03.004

Glasserman, P., & Young, H. P. (2016). Contagion in financial networks. *Journal of Economic Literature*, *54*(3), 779–831. https://doi.org/10.1257/jel.20151228

Gong, X., Liu, Y., & Wang, X. (2021). Dynamic volatility spillovers across oil and natural gas futures markets based on a time-varying spillover method. *International Review of Financial Analysis*, *76*, Article 101790. https://doi.org/10.1016/j.irfa.2021.101790

Gropp, R., & Moerman, G. (2004). Measurement of contagion in banks' equity prices. *Journal of International Money and Finance*, 23(3), 405–459. https://doi.org/10.1016/j.jimonfin.2004.01.005

Gunay, S. (2020). *A new form of financial contagion*: *COVID-19 and stock market responses*. SSRN. https://doi.org/10.2139/ssrn.3584243

Gupta, A., & Mishra, R. (2024). A comprehensive study of stock market volatility: Types, determinants, and measurement methods. *International Journal for Multidisciplinary Research*, *6*(6), Article 30054. https://doi.org/10.36948/ijfmr.2024.v06i06.30054

Hautsch, N., Schaumburg, J., & Schienle, M. (2015). Financial network systemic risk contributions. *Review of Finance*, *19*(2), 685–738. https://doi.org/10.1093/rof/rfu010

Kang, S. H., & Lee, J. W. (2019). The network connectedness of volatility spillovers across global futures markets. *Physica A*: *Statistical Mechanics and its Applications*, *526*, Article 120756. https://doi.org/10.1016/j.physa.2019.03.121

Karimalis, E. N., & Nomikos, N. K. (2017). Measuring systemic risk in the European banking sector: a copula *CoVaR* approach. *The European Journal of Finance*, *24*(11), 944–975. https://doi.org/10.1080/1351847X.2017.1366350

Karkowska, R., & Urjasz, S. (2021). Connectedness structures of sovereign bond markets in Central and Eastern Europe. *International Review of Financial Analysis*, *74*, Article 101644. https://doi.org/10.1016/j.irfa.2020.101644

King, M., Sentana, E., & Wadhwani, S. (1994). Volatility and links between national stock markets. *Econometrica*, *62*(4), Article 901. https://doi.org/10.2307/2951737

Maghyereh, A. I., Awartani, B., & Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. *Energy Economics*, *57*, 78–93. https://doi.org/10.1016/j.eneco.2016.04.010

Maurya, P. K., Bansal, R., & Mishra, A. K. (2024). Dynamic connectedness among market volatilities: A perspective of COVID-19 and Russia-Ukraine conflict. *Studies in Economics and Finance*, *41*(5), 1119–1140. https://doi.org/10.1108/SEF-01-2024-0029

Mérő, K., & Bethlendi, A. (2022). Financial markets: Banks and capital markets. In L. Mátyás (Ed.), *Emerging European economies after the pandemic*: *Stuck in the middle income trap?* (pp. 53–111). Springer International Publishing. https://doi.org/10.1007/978-3-030-93963-2_2

Mérő, K., & Piroska, D. (2016). Banking Union and banking nationalism – Explaining opt-out choices of Hungary, Poland and the Czech Republic. *Policy and Society*, *35*(3), 215–226. https://doi.org/10.1016/j.polsoc.2016.10.001

Mieg, H. A. (2022). Volatility as a transmitter of systemic risk: Is there a structural risk in finance? *Risk Analysis*, *42*(9), 1952–1964. https://doi.org/10.1111/risa.13564

Nerantzidis, M., Stoupos, N., & Tzeremes, P. (2024). Realized volatility spillover connectedness among the leading European currencies after the end of the sovereign-debt crisis: A QVAR approach. *Journal of Risk and Financial Management*, *17*(8), Article 8. https://doi.org/10.3390/jrfm17080337

Onwumere, J. U. J., Braimah, A. G., & Idolor, E. J. (2018). Volatility transmission and spillovers: A review of literature. *Accounting and Taxation Review*, *2*(1), 199–232. http://www.zbw.eu/econis-archiv/handle/11159/4383

Paltalidis, N., Gounopoulos, D., Kizys, R., & Koutelidakis, Y. (2015). Transmission channels of systemic risk and contagion in the European financial network. *Journal of Banking & Finance*, *61*, S36–S52. https://doi.org/10.1016/j.jbankfin.2015.03.021

Pan, Q., & Sun, Y. (2023). Changes in volatility leverage and spillover effects of crude oil futures markets affected by the 2022 Russia-Ukraine conflict. *Finance Research Letters*, *58*, Article 104442. https://doi.org/10.1016/j.frl.2023.104442

Piroska, D., Gorelkina, Y., & Johnson, J. (2021). Macroprudential policy on an uneven playing field: Supranational regulation and domestic politics in the EU's dependent market economies. *JCMS*: *Journal of Common Market Studies*, *59*, 497–517. https://doi.org/10.1111/jcms.13097

Prorokowski, L. (2013). Lessons from financial crisis contagion simulation in Europe. *Studies in Economics and Finance*, *30*(2), 159–188. https://doi.org/10.1108/10867371311325453

Shahzad, S. J. H., Hernandez, J. A., Rehman, M. U., Al-Yahyaee, K. H., & Zakaria, M. (2018). A global network topology of stock markets: Transmitters and receivers of spillover effects. *Physica A*: *Statistical Mechanics and its Applications*, *492*, 2136–2153. https://doi.org/10.1016/j.physa.2017.11.132

Shahzad, S. J. H., Hoang, T. H. V., & Arreola-Hernandez, J. (2019). Risk spillovers between large banks and the financial sector: Asymmetric evidence from Europe. *Finance Research Letters*, *28*, 153–159. https://doi.org/10.1016/j.frl.2018.04.008

Vidal-Llana, X., Uribe, J. M., & Guillén, M. (2023). European stock market volatility connectedness: The role of country and sector membership. *Journal of International Financial Markets*, *Institutions and Money*, *82*, Article 101696. https://doi.org/10.1016/j.intfin.2022.101696

Vukovic, D. B., Lapshina, K. A., & Maiti, M. (2021). Wavelet coherence analysis of returns, volatility and interdependence of the US and the EU money markets: Pre & post crisis. *The North American Journal of Economics and Finance*, *58*, Article 101457. https://doi.org/10.1016/j.najef.2021.101457

Wang, G.-J., Feng, Y., Xiao, Y., Zhu, Y., & Xie, C. (2022). Connectedness and systemic risk of the banking industry along the Belt and Road. *Journal of Management Science and Engineering*, *7*(2), 303–329. https://doi.org/10.1016/j.jmse.2021.12.002

Wang, G.-J., Xie, C., Zhao, L., & Jiang, Z.-Q. (2018). Volatility connectedness in the Chinese banking system: Do state-owned commercial banks contribute more? *Journal of International Financial Markets*, *Institutions and Money*, *57*, 205–230. https://doi.org/10.1016/j.intfin.2018.07.008

Yilmaz, K. (2010). Return and volatility spillovers among the East Asian equity markets. *Journal of Asian Economics*, *21*(3), 304–313. https://doi.org/10.1016/j.asieco.2009.09.001

APPENDIX

Table A1. Descriptive Statistics I

Bank	Mean	Median	Max	Min	Std Dev
KOMB.K	0.010	0.007	0.116	0.000	0.011
BRD.K	0.011	0.008	0.182	0.000	0.012
TLV.K	0.011	0.007	0.222	0.000	0.013
SWED.N	0.011	0.008	0.151	0.000	0.012
DNB.N	0.011	0.008	0.134	0.000	0.012
OTP.K	0.014	0.010	0.242	0.000	0.015
ING.K	0.014	0.010	0.124	0.000	0.014
BHW.K	0.014	0.010	0.160	0.000	0.014
KBC.NK	0.014	0.010	0.268	0.000	0.016
ACA.N	0.014	0.010	0.212	0.000	0.015
INGA.N	0.014	0.010	0.243	0.000	0.017
BNP.N	0.015	0.010	0.256	0.000	0.016
PEO.K	0.015	0.011	0.218	0.000	0.015
PKO.K	0.015	0.011	0.184	0.000	0.015
ISP.NK	0.015	0.010	0.376	0.000	0.017
BBVA.N	0.015	0.011	0.193	0.000	0.016
EBS.K	0.015	0.011	0.180	0.000	0.017
SAN.N	0.015	0.011	0.247	0.000	0.016
BOS.K	0.016	0.011	0.169	0.000	0.018
CABK.N	0.016	0.012	0.216	0.000	0.016
GLE.N	0.016	0.011	0.318	0.000	0.019
RBI.K	0.018	0.013	0.263	0.000	0.019
DBK.N	0.018	0.013	0.216	0.000	0.019
ALR.K	0.018	0.013	0.222	0.000	0.019
MBK.K	0.019	0.014	0.216	0.000	0.019
CBK.N	0.019	0.014	0.238	0.000	0.020
SAB.N	0.019	0.014	0.252	0.000	0.021
UCG.NK	0.020	0.014	0.356	0.000	0.021
MIL.K	0.020	0.014	0.240	0.000	0.020
ALPHA.K	0.029	0.019	0.447	0.000	0.035

Table A2. Descriptive Statistics II

Bank	Skewness	Kurtosis	Jarque-Bera	ADF
KOMB.K	2.871	17.194	22801***	–7.548***
BRD.K	3.460	31.702	84774***	–10.339***
TLV.K	5.209	58.316	308129***	–6.457***
SWED.N	3.725	28.010	66227***	–6.034***
DNB.N	2.743	15.795	18848***	–6.509***
OTP.K	4.409	42.300	157760***	–7.685***
ING.K	2.286	11.315	8756***	–6.052***
BHW.K	2.205	13.131	11873***	–6.946***
KBC.NK	4.655	51.044	232905***	–7.848***
ACA.N	3.870	32.607	91075***	–8.190***
INGA.N	4.163	36.923	118651***	–7.029***
BNP.N	4.144	40.218	141391***	–8.102***
PEO.K	3.618	30.414	78180***	–6.906***
PKO.K	2.886	20.051	31515***	–5.602***
ISP.NK	6.064	95.626	848662***	–6.387***
BBVA.N	3.219	22.335	40388***	–8.583***
EBS.K	3.337	21.559	37829***	–8.288***
SAN.N	3.960	35.810	110785***	–5.787***
BOS.K	2.892	16.607	21260***	–7.392***
CABK.N	2.969	22.563	40648***	–10.940***
GLE.N	4.564	45.398	182919***	–7.826***
RBI.K	3.379	25.011	51556***	–7.507***
DBK.N	3.038	19.743	30851***	–4.952***
ALR.K	3.189	21.270	36418***	–5.421***
MBK.K	2.806	18.029	25029***	–10.248***
CBK.N	3.006	19.716	30687***	–8.722***
SAB.N	3.306	22.454	41057***	–6.590***
UCG.NK	3.991	40.490	142883***	–10.315***
MIL.K	2.973	19.784	30834***	–7.064***
ALPHA.K	3.922	28.955	71494***	–7.129***

Table A3. Results for the period 2014–2019

	OTP.K	EBS.K	RBI.K	PKO.K	PEO.K	BHW.K	MIL.K	ALR.K	KOMB.K	BOS.K	TLV.K	ING.K	MBK.K	ALPHA.K	BRD.K	DBK.N	CBK.N	BNP.N	GLE.N	ACA.N	INGA.N	SAB.N	SAN.N	BBVA.N	ISP.NK	UCG.NK	KBC.NK	CABK.N	DNB.N	SWED.N	FROM
OTP.K	30.23	1.69	4.63	1.46	0.35	1.00	0.97	0.47	0.44	0.09	0.44	0.45	0.95	11.17	0.30	2.66	3.26	3.05	3.95	2.54	3.37	2.74	3.43	2.30	5.87	4.74	3.45	2.38	0.85	0.78	69.77
EBS.K	0.36	21.42	4.83	0.45	0.20	0.36	0.56	0.30	0.37	0.06	0.28	0.25	0.43	6.27	0.25	3.65	4.34	4.11	6.02	3.56	4.20	4.77	4.34	3.38	7.08	8.86	4.22	3.37	0.80	0.89	78.58
RBI.K	0.77	3.56	37.39	0.52	0.20	0.17	0.49	0.32	0.28	0.04	0.13	0.16	0.37	7.30	0.12	2.96	3.56	2.88	4.15	3.57	3.39	3.49	3.46	2.67	4.77	6.60	2.77	2.36	0.91	0.64	62.61
PKO.K	1.22	1.46	1.98	32.19	3.37	1.76	7.43	3.53	0.26	0.57	0.11	0.89	5.48	7.91	0.12	2.07	1.81	2.24	3.44	1.62	2.96	1.37	2.87	1.67	3.44	3.71	1.97	1.45	0.62	0.48	67.81
PEO.K	0.66	0.97	1.83	8.39	44.32	3.65	3.63	3.59	0.21	0.32	0.10	1.30	4.68	2.07	0.26	1.89	1.47	1.42	2.36	1.21	2.17	0.71	1.76	1.01	2.92	3.57	1.16	0.94	0.92	0.51	55.68
BHW.K	0.87	0.97	0.87	2.15	1.45	44.89	2.48	1.83	0.58	0.93	0.26	1.92	2.49	6.59	0.22	1.97	1.54	1.46	4.12	1.49	2.85	2.19	2.55	1.47	3.64	3.32	2.08	1.80	0.64	0.40	55.11
MIL.K	0.44	0.98	1.38	4.08	0.80	1.31	61.17	1.49	0.04	0.19	0.15	0.60	4.90	3.43	0.05	0.85	1.36	1.20	2.08	0.88	1.57	1.22	1.37	1.16	2.33	2.26	1.42	0.92	0.15	0.22	38.83
ALR.K	0.31	0.67	1.05	2.56	1.27	1.34	1.71	57.03	0.35	0.57	0.10	0.78	1.75	3.20	0.00	2.40	2.14	1.80	2.81	1.81	1.83	2.03	2.03	1.37	2.45	2.67	1.39	1.69	0.63	0.25	42.97
KOMB.K	0.75	2.42	3.04	0.82	0.22	1.37	0.41	1.01	22.03	0.04	0.23	0.95	0.20	17.80	0.12	2.39	3.01	2.87	5.27	3.44	4.87	3.61	3.72	2.07	5.06	5.35	2.65	2.55	1.17	0.54	77.97
BOS.K	0.10	0.14	0.15	0.52	0.19	0.65	0.32	0.70	0.00	90.71	0.16	0.21	0.77	1.10	0.15	0.72	0.26	0.20	0.70	0.27	0.19	0.19	0.19	0.11	0.40	0.53	0.17	0.00	0.06	0.14	9.29
TLV.K	0.46	0.66	0.66	0.11	0.01	0.24	0.32	0.09	0.16	0.40	74.67	0.01	0.21	6.52	10.85	0.29	0.12	0.38	0.72	0.23	0.20	0.62	0.32	0.07	0.42	0.50	0.10	0.39	0.14	0.13	25.33
ING.K	0.48	1.12	1.21	1.41	0.90	2.80	1.34	1.42	0.55	0.30	0.19	36.50	1.97	10.93	0.10	2.23	2.11	2.24	3.42	2.68	2.78	1.63	2.43	1.76	5.57	7.37	2.41	1.28	0.60	0.28	63.50
MBK.K	0.47	1.18	1.60	4.51	1.41	1.92	7.34	1.86	0.06	0.45	0.23	1.11	47.39	4.13	0.13	2.61	2.24	2.04	2.80	1.47	1.77	1.16	2.00	1.42	1.91	2.56	1.90	1.58	0.24	0.49	52.61
ALPHA.K	0.19	0.50	0.55	0.20	0.01	0.13	0.14	0.12	0.16	0.04	0.16	0.16	0.10	85.59	0.05	0.80	0.73	0.80	1.16	0.82	1.11	0.59	0.76	0.49	1.56	1.49	0.55	0.57	0.34	0.10	14.41
BRD.K	0.56	2.21	1.47	0.38	0.32	0.46	0.18	0.22	0.22	0.44	18.40	0.07	0.26	6.80	48.24	1.27	1.18	1.07	2.41	0.81	1.53	1.14	1.13	1.01	2.02	2.60	1.06	1.74	0.24	0.56	51.76
DBK.N	0.29	1.74	1.87	0.31	0.11	0.26	0.22	0.39	0.17	0.07	0.07	0.18	0.45	4.80	0.15	20.11	8.43	4.76	7.10	4.49	4.59	4.45	5.90	4.64	6.40	9.53	2.94	3.45	1.27	0.85	79.89
CBK.N	0.37	2.05	2.28	0.27	0.09	0.21	0.33	0.37	0.23	0.05	0.04	0.20	0.40	4.45	0.12	8.60	19.40	4.35	6.63	4.53	4.57	5.08	5.16	4.26	6.77	9.88	3.53	3.82	0.84	1.08	80.60
BNP.N	0.42	2.55	2.31	0.43	0.11	0.28	0.33	0.46	0.28	0.04	0.08	0.31	0.44	5.93	0.11	6.31	5.64	8.78	8.93	5.44	5.70	4.93	6.20	4.58	8.56	10.58	4.21	4.04	1.01	1.00	91.22
GLE.N	0.37	2.47	2.23	0.43	0.11	0.39	0.28	0.46	0.37	0.06	0.07	0.29	0.41	6.30	0.12	6.36	5.83	5.95	12.98	5.62	5.53	5.09	5.54	4.41	8.12	10.22	4.02	3.98	1.06	0.93	87.02
ACA.N	0.36	2.14	2.90	0.31	0.09	0.30	0.25	0.43	0.34	0.07	0.04	0.33	0.34	7.28	0.08	5.81	5.76	5.31	8.10	12.45	5.22	5.01	5.41	4.20	7.76	9.26	4.33	3.92	1.16	1.05	87.55
INGA.N	0.41	2.46	2.49	0.56	0.14	0.40	0.45	0.40	0.41	0.06	0.08	0.32	0.39	8.63	0.13	5.76	5.62	5.36	7.72	5.00	10.46	4.56	5.78	4.30	8.28	9.44	4.52	3.70	1.01	1.18	89.54
SAB.N	0.35	2.38	2.25	0.22	0.04	0.30	0.32	0.39	0.27	0.03	0.03	0.18	0.22	3.93	0.04	4.76	5.29	3.90	6.00	4.07	3.86	23.90	5.92	4.43	6.27	7.89	3.55	7.55	0.88	0.79	76.10
SAN.N	0.42	2.17	2.30	0.47	0.11	0.40	0.38	0.43	0.25	0.03	0.04	0.27	0.39	5.01	0.07	6.43	5.48	5.03	6.77	4.53	5.03	6.09	12.06	6.14	8.06	10.43	3.53	5.45	1.25	0.96	87.94
BBVA.N	0.35	2.27	2.41	0.37	0.09	0.30	0.41	0.38	0.23	0.03	0.01	0.28	0.36	4.04	0.05	6.80	6.05	5.01	7.20	4.73	4.99	6.07	8.28	10.51	7.66	10.10	3.43	5.61	1.12	0.85	89.49
ISP.NK	0.46	2.56	2.26	0.40	0.14	0.38	0.42	0.43	0.28	0.08	0.03	0.45	0.27	6.80	0.09	4.89	4.98	4.77	6.67	4.42	4.95	4.44	5.53	3.92	17.44	13.82	4.16	3.51	0.82	0.64	82.56
UCG.NK	0.25	2.37	2.31	0.29	0.09	0.25	0.27	0.29	0.22	0.04	0.04	0.38	0.24	4.74	0.07	5.49	5.50	4.45	6.40	4.08	4.25	4.20	5.40	3.93	10.47	25.39	3.36	3.81	0.81	0.60	74.61
KBC.NK	0.51	3.06	2.79	0.46	0.11	0.44	0.52	0.43	0.30	0.14	0.03	0.43	0.51	6.05	0.12	4.77	5.53	4.99	7.26	5.50	5.79	5.27	5.21	3.78	8.98	9.79	10.97	4.03	0.94	1.29	89.03
CABK.N	0.33	2.20	2.09	0.30	0.07	0.38	0.34	0.42	0.21	0.00	0.02	0.19	0.39	4.00	0.05	4.90	5.27	4.22	6.31	4.31	4.19	9.99	7.12	5.52	6.77	9.57	3.48	15.46	1.06	0.85	84.54
DNB.N	0.47	1.80	3.06	0.50	0.18	0.53	0.20	0.60	0.37	0.07	0.08	0.39	0.22	10.35	0.10	6.52	3.93	3.68	6.09	4.47	4.00	4.08	5.88	3.82	5.65	7.07	2.80	3.65	17.60	1.86	82.40
SWED.N	0.55	2.39	2.30	0.40	0.17	0.35	0.30	0.23	0.25	0.33	0.10	0.10	0.34	5.64	0.08	5.18	6.04	4.33	5.97	4.65	5.26	4.26	5.14	3.36	5.03	6.57	4.71	3.61	2.07	20.28	79.72
TO	13.55	53.16	61.11	33.27	12.35	22.30	32.34	23.06	7.84	5.55	21.69	13.17	29.93	183.18	14.10	111.36	108.47	93.88	142.57	92.25	102.73	100.99	114.80	83.27	154.24	190.29	79.88	83.16	23.61	20.33	2028.45
ALL	43.78	74.57	98.50	65.46	56.67	67.19	93.51	80.09	29.88	96.26	96.36	49.67	77.32	268.77	62.34	131.47	127.88	102.66	155.55	104.70	113.19	124.89	126.86	93.78	171.68	215.68	90.85	98.62	41.21	40.62	**TVC**
NET	–56.22	–25.43	–1.50	–34.54	–43.33	–32.81	–6.49	–19.91	–70.12	–3.74	–3.64	–50.33	–22.68	168.77	–37.66	31.47	27.88	2.66	55.55	4.70	13.19	24.89	26.86	–6.22	71.68	115.68	–9.15	–1.38	–58.79	–59.38	67.62

Table A4. Results for the period 2020–2021

	OTP.K	EBS.K	RBI.K	PKO.K	PEO.K	BHW.K	MIL.K	ALR.K	KOMB.K	BOS.K	TLV.K	ING.K	MBK.K	ALPHA.K	BRD.K	DBK.N	CBK.N	BNP.N	GLE.N	ACA.N	INGA.N	SAB.N	SAN.N	BBVA.N	ISP.NK	UCG.NK	KBC.NK	CABK.N	DNB.N	SWED.N	FROM
OTP.K	11.03	2.77	2.27	1.96	2.64	0.13	4.35	3.66	0.69	1.55	1.94	1.34	2.67	7.15	1.33	3.57	5.10	4.88	6.68	3.74	3.44	3.65	3.66	3.25	2.97	2.83	3.17	2.63	2.87	2.07	88.97
EBS.K	1.13	7.87	3.53	1.60	1.77	0.29	2.83	2.15	1.03	0.89	1.01	0.90	1.53	6.31	0.81	3.28	5.07	5.90	7.41	4.62	6.11	5.40	5.00	5.23	2.67	4.05	4.80	3.25	2.04	1.50	92.13
RBI.K	0.96	4.94	8.74	1.85	1.82	0.28	2.35	2.32	1.24	1.07	0.81	1.46	1.95	5.36	0.65	2.70	4.54	5.53	6.96	4.37	6.85	5.85	4.78	4.22	3.04	4.19	4.56	3.50	1.95	1.17	91.26
PKO.K	1.23	2.31	2.12	9.27	6.22	0.66	7.99	7.30	1.06	2.70	0.86	2.41	6.08	5.96	0.78	2.44	3.14	3.27	4.45	3.30	3.96	3.91	3.01	3.13	2.20	2.64	2.45	2.22	1.78	1.17	90.73
PEO.K	1.71	1.96	1.77	4.86	10.95	0.86	7.28	7.36	0.95	2.94	1.03	1.93	4.72	5.72	0.84	2.28	3.76	3.36	5.03	3.54	3.81	3.35	2.94	3.09	2.66	2.86	3.26	2.12	1.85	1.24	89.05
BHW.K	0.91	1.90	1.31	2.86	4.57	20.31	10.07	6.75	1.25	3.30	0.42	2.29	6.38	5.62	0.52	1.37	2.79	2.23	2.94	1.89	2.22	4.77	2.15	2.21	1.55	1.67	2.06	1.14	1.63	0.91	79.69
MIL.K	1.30	1.40	1.41	3.93	4.93	1.16	22.99	8.27	0.83	3.99	0.65	2.32	9.19	5.02	0.50	1.68	3.12	2.53	2.99	2.45	2.19	2.34	2.06	2.00	1.78	1.88	2.73	1.63	1.44	1.31	77.01
ALR.K	1.12	1.38	1.45	3.92	5.16	0.88	8.71	29.44	0.82	3.69	1.26	2.32	5.87	4.65	0.82	2.16	2.35	1.94	2.44	2.09	2.08	1.67	2.02	2.14	2.05	1.65	2.03	1.22	1.64	1.05	70.56
KOMB.K	1.29	3.55	3.10	2.15	2.70	0.63	3.80	3.65	5.81	1.19	1.19	1.52	3.04	11.99	0.83	1.76	3.58	4.25	6.20	3.19	4.89	5.12	4.93	4.23	2.72	3.41	3.41	2.68	1.68	1.50	94.19
BOS.K	0.75	1.09	1.23	3.02	3.57	1.11	8.65	7.42	0.50	38.43	0.58	2.21	5.39	3.85	0.50	1.50	2.76	1.36	1.99	1.80	1.38	2.00	1.44	1.70	1.42	1.08	0.83	0.91	1.10	0.44	61.57
TLV.K	2.17	3.28	2.16	2.08	2.95	0.11	3.38	6.29	1.25	1.45	8.56	2.01	2.03	9.27	2.84	2.38	3.82	4.90	5.96	3.81	3.30	2.89	3.15	3.79	2.73	3.27	3.51	2.07	2.85	1.77	91.44
ING.K	1.26	1.54	2.22	3.68	3.47	0.79	7.15	6.85	1.11	3.02	0.81	18.86	5.58	6.22	0.66	1.25	2.19	3.23	4.12	2.52	2.95	3.54	1.84	3.24	2.03	2.43	2.56	2.06	1.73	1.09	81.14
MBK.K	1.11	1.28	1.72	3.17	3.26	0.90	10.04	6.24	0.87	2.33	0.59	2.18	23.23	8.07	0.56	1.03	2.51	2.78	3.95	2.86	2.05	3.62	2.69	2.88	1.75	2.02	1.96	2.05	1.40	0.89	76.77
ALPHA.K	1.02	1.96	1.55	1.14	1.59	0.26	2.33	1.68	1.04	0.56	0.77	0.83	2.72	38.11	0.76	1.64	2.98	3.79	6.03	2.92	2.94	4.90	3.40	3.99	1.85	2.29	2.27	2.13	1.73	0.82	61.89
BRD.K	1.86	3.11	2.11	1.97	2.58	0.25	1.87	3.57	0.90	1.18	3.08	1.50	2.11	8.63	7.57	2.40	4.81	5.70	8.05	5.11	3.56	3.47	3.87	3.86	3.07	4.50	2.73	2.49	2.66	1.43	92.43
DBK.N	1.43	3.23	2.06	1.55	1.84	0.21	2.01	2.79	0.48	1.06	0.82	0.45	1.04	4.62	0.57	14.23	7.42	4.75	7.03	4.63	6.63	3.75	4.79	4.06	2.96	4.61	4.02	3.06	2.37	1.53	85.77
CBK.N	1.25	3.35	2.24	1.38	1.77	0.29	2.34	1.74	0.66	0.99	0.77	0.55	1.74	5.91	0.72	4.71	13.27	5.37	7.64	4.70	5.88	5.31	5.19	4.60	3.09	4.01	3.59	3.84	1.75	1.37	86.73
BNP.N	0.88	3.87	2.65	1.31	1.70	0.21	2.02	1.27	0.74	0.55	0.90	0.68	1.74	7.12	0.86	3.08	5.38	9.78	8.96	5.38	6.28	5.41	5.56	5.37	3.18	4.09	4.20	3.50	2.07	1.24	90.22
GLE.N	1.40	3.49	2.48	1.31	1.81	0.20	1.73	1.34	0.74	0.67	0.85	0.71	1.73	7.86	0.87	3.38	5.54	6.53	11.89	5.25	5.95	5.88	5.56	5.18	3.33	4.15	3.59	3.43	1.92	1.24	88.11
ACA.N	1.16	3.59	2.60	1.57	2.05	0.21	2.26	1.96	0.72	0.83	0.87	0.88	2.02	6.43	0.94	3.54	5.71	6.34	8.58	7.46	6.26	4.65	5.41	4.88	3.24	4.68	4.34	3.41	2.03	1.38	92.54
INGA.N	0.89	3.92	3.06	1.54	1.85	0.24	1.70	1.49	0.94	0.56	0.69	0.85	1.21	5.55	0.54	3.98	5.69	5.90	7.73	4.98	12.11	5.22	5.47	4.86	3.40	4.42	4.94	3.25	1.82	1.21	87.89
SAB.N	0.96	2.71	2.06	1.34	1.40	0.28	2.02	1.14	0.67	0.61	0.45	0.56	2.08	6.15	0.40	1.99	4.37	4.17	6.25	3.03	4.17	27.58	5.01	6.46	1.94	3.07	2.48	4.21	1.34	1.08	72.42
SAN.N	0.81	3.46	2.43	1.37	1.63	0.25	2.00	1.61	0.97	0.62	0.55	0.56	2.10	6.12	0.63	3.23	5.54	5.92	8.09	4.91	6.18	7.06	9.62	6.69	3.08	4.53	3.59	3.78	1.47	1.23	90.38
BBVA.N	0.84	3.48	2.06	1.41	1.66	0.24	1.81	1.70	0.78	0.73	0.75	0.78	2.16	7.43	0.63	2.74	4.83	5.66	7.44	4.22	5.28	8.91	6.41	11.88	2.74	3.45	3.51	3.88	1.64	0.95	88.12
ISP.NK	1.33	2.92	2.53	1.66	2.45	0.27	2.54	2.77	0.81	1.04	0.90	1.06	1.94	5.93	0.78	3.33	5.74	5.83	8.01	4.89	6.48	4.65	5.22	4.70	6.26	5.17	4.13	3.01	2.07	1.58	93.74
UCG.NK	1.23	3.29	2.66	1.45	1.98	0.20	1.80	1.94	0.78	0.67	0.79	0.90	1.67	4.95	0.85	3.92	5.46	5.23	7.53	5.12	6.06	5.39	5.45	4.35	3.87	10.96	4.65	3.35	2.02	1.45	89.04
KBC.NK	1.20	4.11	2.98	1.42	2.19	0.23	2.47	1.77	0.82	0.72	0.80	0.87	1.04	6.00	0.55	3.43	4.91	5.75	6.91	4.88	6.95	4.66	4.69	4.61	3.09	4.64	11.55	3.44	1.87	1.44	88.45
CABK.N	1.08	3.37	2.62	1.43	1.68	0.18	2.14	1.35	0.76	0.70	0.64	0.85	2.06	6.19	0.59	3.08	6.05	5.58	7.36	4.39	5.27	8.64	5.57	6.00	2.57	3.94	3.88	9.12	1.70	1.20	90.88
DNB.N	1.51	3.46	2.61	1.90	2.29	0.32	2.72	2.85	0.67	1.21	1.33	1.13	2.13	9.09	1.16	3.95	4.55	5.45	6.70	4.38	5.19	4.94	3.63	4.34	2.73	3.95	3.57	2.78	7.60	1.85	92.40
SWED.N	1.80	3.30	2.28	1.91	2.76	0.30	4.28	3.28	0.92	0.81	0.97	1.31	2.01	5.66	0.79	3.71	5.65	4.69	6.31	4.68	4.79	4.44	4.30	3.40	3.15	4.17	4.75	3.15	2.77	7.67	92.33
TO	35.60	84.02	65.26	60.73	76.29	11.97	114.65	102.48	25.01	41.62	27.08	37.36	85.93	188.85	23.27	79.50	129.35	132.81	179.76	113.66	133.10	135.36	119.19	118.45	76.86	99.65	97.56	80.18	55.19	37.13	2567.84
ALL	46.63	91.89	74.00	70.00	87.23	32.28	137.64	131.92	30.82	80.05	35.63	56.22	109.15	226.96	30.84	93.72	142.62	142.59	191.66	121.12	145.22	162.93	128.82	130.33	83.12	110.61	109.11	89.30	62.79	44.80	**TVC**
NET	−53.37	−8.11	−26.00	−30.00	−12.77	−67.72	37.64	31.92	−69.18	−19.95	−64.37	−43.78	9.15	126.96	−69.16	−6.28	42.62	42.59	91.66	21.12	45.22	62.93	28.82	30.33	−16.88	10.61	9.11	−10.70	−37.21	−55.20	85.59

Table A5. Results for the period 2022–2023

	OTP.K	EBS.K	RBI.K	PKO.K	PEO.K	BHW.K	MIL.K	ALR.K	KOMB.K	BOS.K	TLV.K	ING.K	MBK.K	ALPHA.K	BRD.K	DBK.N	CBK.N	BNP.N	GLE.N	ACA.N	INGA.N	SAB.N	SAN.N	BBVA.N	ISP.NK	UCG.NK	KBC.NK	CABK.N	DNB.N	SWED.N	FROM
OTP.K	24.09	5.77	9.04	3.50	4.86	1.67	3.27	4.51	1.56	1.72	0.13	0.78	2.65	1.73	0.56	3.40	3.95	2.88	5.16	2.05	3.08	1.62	1.29	1.39	2.41	4.20	1.32	0.68	0.44	0.28	75.91
EBS.K	4.58	12.87	8.42	2.98	3.02	0.90	3.25	3.82	1.53	1.16	0.31	0.90	2.08	2.03	0.33	5.67	7.66	3.63	6.23	2.33	4.15	3.30	2.29	2.14	3.28	5.10	2.51	2.11	0.55	0.88	87.13
RBI.K	4.24	5.98	22.79	3.23	3.21	1.11	4.83	3.58	1.30	1.59	0.29	0.61	2.31	1.43	0.32	5.20	6.38	3.04	5.43	1.94	3.10	2.54	2.09	1.90	2.69	4.98	1.66	1.10	0.61	0.50	77.21
PKO.K	2.91	3.48	5.10	14.16	11.57	2.10	8.09	8.09	1.78	1.86	0.16	1.73	6.78	1.28	0.32	3.85	4.22	1.46	2.91	1.17	2.40	2.07	1.94	1.96	1.63	3.09	1.14	1.23	0.82	0.68	85.84
PEO.K	3.46	3.21	4.83	10.34	16.62	2.03	7.36	9.15	1.65	1.99	0.19	1.77	6.65	1.33	0.21	2.94	3.34	1.41	2.72	1.31	2.47	2.12	1.85	1.85	2.05	3.83	0.94	1.12	0.69	0.57	83.38
BHW.K	3.09	2.88	5.31	6.04	6.28	17.90	8.22	6.40	1.96	3.51	0.35	2.26	6.46	0.86	0.31	3.83	3.14	1.45	2.78	1.09	2.21	1.76	1.41	1.72	1.97	3.87	0.77	0.70	0.72	0.75	82.10
MIL.K	1.99	2.62	5.70	5.78	6.06	1.85	25.85	9.62	0.99	2.92	0.28	1.58	7.05	0.53	0.33	2.92	3.79	1.27	2.68	0.93	1.92	1.73	1.71	1.72	1.70	3.89	0.75	0.74	0.67	0.41	74.15
ALR.K	2.69	3.54	4.71	6.34	7.59	1.63	9.97	21.71	1.31	2.43	0.15	1.74	7.14	0.83	0.23	3.75	3.91	1.37	2.39	1.04	1.79	1.89	1.85	2.09	1.78	3.09	0.98	1.01	0.62	0.43	78.29
KOMB.K	3.27	5.65	6.28	5.32	5.53	1.96	4.39	5.67	12.19	2.86	0.36	0.93	4.91	2.19	0.66	4.97	3.81	1.77	4.52	1.41	3.06	2.98	1.87	1.84	2.30	3.76	1.43	1.94	1.06	1.13	87.81
BOS.K	1.84	1.89	3.93	3.82	4.81	2.76	9.29	7.76	1.78	31.69	0.36	0.74	6.00	0.52	0.67	2.69	2.60	1.26	2.31	1.09	1.99	1.28	0.87	0.92	1.32	3.01	0.91	0.68	0.67	0.56	68.31
TLV.K	3.28	5.26	5.58	1.56	2.44	0.70	4.64	1.79	2.12	1.53	23.19	0.44	4.16	1.95	4.67	2.88	3.37	2.68	4.10	2.16	3.31	1.87	1.74	1.34	2.57	5.40	2.65	1.16	0.38	1.08	76.81
ING.K	1.33	3.34	3.20	5.51	6.51	2.12	6.78	6.51	1.27	1.37	0.18	35.95	4.83	0.73	0.21	1.96	2.06	1.10	1.84	0.74	1.22	2.15	1.32	1.22	0.93	2.76	0.70	1.33	0.51	0.30	64.05
MBK.K	2.05	2.33	3.70	6.76	7.63	1.98	9.74	9.62	1.55	2.58	0.35	1.56	22.68	0.56	0.37	3.32	3.38	1.28	2.79	0.98	1.69	1.95	1.73	1.57	1.71	3.05	0.95	1.13	0.66	0.34	77.32
ALPHA.K	2.91	5.40	4.75	2.91	3.52	0.72	1.45	3.09	1.48	0.49	0.30	0.61	1.01	30.66	0.31	3.53	4.11	2.45	4.64	1.38	3.41	4.56	1.82	2.09	2.52	4.31	1.53	2.73	0.42	0.90	69.34
BRD.K	4.04	3.72	4.55	2.46	2.00	0.50	4.55	2.14	1.78	2.86	4.21	0.05	3.16	1.21	29.77	3.09	4.19	2.21	4.64	2.47	2.91	2.04	1.28	1.17	2.59	2.58	0.96	1.30	0.71	0.87	70.23
DBK.N	2.07	4.77	5.79	2.83	2.39	0.86	2.73	3.44	0.89	0.88	0.19	0.39	2.30	0.94	0.19	17.52	11.34	3.64	5.89	1.99	3.87	4.83	3.76	2.63	3.11	5.09	1.84	2.38	0.73	0.71	82.48
CBK.N	2.11	5.19	6.02	2.55	2.29	0.66	3.04	3.02	0.82	0.60	0.18	0.43	2.10	0.95	0.23	8.93	21.84	2.96	5.57	1.93	3.63	4.80	3.18	2.44	3.13	5.47	2.07	2.78	0.49	0.58	78.16
BNP.N	3.43	6.03	6.57	2.14	2.39	0.71	2.36	2.52	0.91	0.84	0.31	0.43	1.85	1.29	0.27	7.11	6.95	8.05	8.87	3.60	5.82	4.16	3.31	3.39	4.75	5.62	2.81	2.09	0.54	0.90	91.95
GLE.N	3.42	5.95	6.90	2.34	2.50	0.78	3.09	2.64	1.13	0.89	0.34	0.46	2.29	1.51	0.38	6.58	7.57	5.24	13.77	3.42	4.74	3.86	2.47	2.51	4.17	5.54	2.31	1.87	0.60	0.73	86.23
ACA.N	3.91	6.02	6.39	2.40	3.16	0.81	2.68	3.01	1.00	1.06	0.40	0.60	2.01	1.33	0.51	5.73	6.92	5.50	8.71	6.89	5.77	3.45	2.80	2.72	4.89	5.69	2.52	1.82	0.48	0.81	93.11
INGA.N	3.88	5.68	6.01	2.75	3.40	0.83	2.93	2.74	1.24	1.11	0.27	0.38	1.95	1.80	0.31	6.19	7.12	4.84	6.88	3.23	9.79	4.10	3.25	3.03	4.51	5.57	2.55	2.12	0.61	0.94	90.21
SAB.N	1.38	3.90	3.80	1.92	2.50	0.76	2.07	2.15	0.95	0.61	0.15	0.55	1.69	1.81	0.19	6.94	7.87	2.86	4.43	1.46	3.36	20.43	4.18	3.52	3.55	6.65	1.57	6.91	0.62	1.21	79.57
SAN.N	1.77	4.12	4.99	3.09	3.42	0.77	3.67	3.73	0.92	0.88	0.24	0.59	2.71	1.21	0.15	7.72	8.23	3.72	4.65	2.05	4.53	6.70	9.22	4.74	3.77	5.47	1.96	3.45	0.80	0.73	90.78
BBVA.N	2.15	4.24	4.83	3.30	3.56	0.99	3.75	4.41	1.10	0.60	0.17	0.65	2.56	1.07	0.12	6.18	7.01	4.02	5.15	2.07	4.52	6.07	5.05	10.65	3.95	5.49	1.99	2.77	0.66	0.90	89.35
ISP.NK	2.42	5.37	5.40	2.27	3.15	0.89	3.18	3.43	1.07	0.88	0.27	0.40	2.29	1.37	0.33	5.69	7.01	4.50	6.58	3.04	5.22	4.70	3.19	3.17	9.18	8.68	2.11	2.62	0.53	1.04	90.82
UCG.NK	2.52	4.68	6.05	2.55	3.41	1.09	4.42	3.64	0.81	1.04	0.34	0.70	2.39	1.37	0.18	5.64	7.52	3.20	5.27	2.11	3.64	5.11	2.75	2.56	5.28	16.56	1.60	2.23	0.45	0.88	83.44
KBC.NK	2.66	6.72	5.78	2.68	2.81	0.52	2.48	3.00	1.26	1.08	0.53	0.51	2.31	1.52	0.28	5.71	8.11	4.44	6.39	2.75	5.10	3.64	2.82	2.62	3.59	4.39	11.98	2.92	0.46	0.93	88.02
CABK.N	1.23	4.54	3.09	2.21	2.43	0.51	1.83	2.37	1.02	0.56	0.22	0.78	2.04	2.15	0.23	6.19	8.85	2.61	4.20	1.49	3.42	13.16	4.21	3.08	3.76	5.44	2.35	14.01	0.67	1.37	85.99
DNB.N	2.10	3.62	5.52	5.22	5.01	1.26	5.60	4.59	2.35	1.71	0.20	0.85	3.41	1.41	0.40	6.31	4.73	2.29	4.37	1.38	3.34	4.76	3.54	2.53	2.65	3.54	1.18	2.24	11.84	2.05	88.16
SWED.N	0.90	5.04	3.59	3.70	3.76	1.41	3.03	3.52	1.56	1.33	0.25	0.45	1.93	2.70	0.38	5.51	4.09	3.17	4.54	1.63	3.93	6.17	1.76	2.42	3.84	5.96	1.97	3.66	1.80	16.03	83.97
TO	77.63	130.92	155.84	108.50	121.21	34.87	132.71	129.94	39.07	42.96	11.69	23.86	99.03	39.60	13.69	144.46	163.23	82.25	136.65	54.23	99.59	109.36	71.33	66.27	86.39	135.53	48.05	58.80	18.99	23.47	2460.14
ALL	101.72	143.79	178.64	122.66	137.83	52.78	158.55	151.65	51.26	74.65	34.88	59.81	121.71	70.26	43.45	161.98	185.07	90.30	150.43	61.12	109.38	129.79	80.55	76.91	95.57	152.09	60.03	72.81	30.83	39.50	TVC
NET	1.72	43.79	78.64	22.66	37.83	–47.22	58.55	51.65	–48.74	–25.35	–65.12	–40.19	21.71	–29.74	–56.55	61.98	85.07	–9.70	50.43	–38.88	9.38	29.79	–19.45	–23.09	–4.43	52.09	–39.97	–27.19	–69.17	–60.50	82.00