Impact of Systemic Risk on Total Capital Ratios of Banks in Europe During Public Debt Crisis, Brexit, Covid-19 Pandemic and the War in Ukraine

Abstract

The paper presents a cross-sectional analysis of systemic risk and its impact on the total capital ratios (TCRs) of 120 systemically important European banks, combining the panel vector autoregression models (VAR) with ΔCoVaR-based systemic risk measurement, investigating the intertwined processes involving a set of 40 exogenous and endogenous variables. The study covers the European public debt crisis, Brexit, the COVID-19 pandemic, and the war in Ukraine. The results offer macroprudential insights. We confirm that in all turbulent periods, systemic risk has a significant positive effect on the TCR in the periods leading to crisis and a strong negative effect in its aftermath. We also find that systemic risk modifies the impact of three macroeconomic indicators (GDP growth, current accounts balance, and public debt), reversing the direction of this impact on the TCR. We further find that banks' ability to build robust capital no longer depends on the housing market dynamics, even when intertwined with a systemic crisis. In contrast, the effect of the US stock market on the TCR is strong and positive in calm periods and equally strong but negative when coupled with systemic turbulence. Thus, our results indicate spillovers of systemic-risk-induced effects on the TCR between the US and Europe for both listed and unlisted banks. Importantly, we present empirical evidence confirming that the war in Ukraine affects banks' TCRs similarly to previous crises.

Keywords: *systemic risk*, *war in Ukraine*, *spillover effects*, *dynamic panel models*, *TCR*.

JEL codes: G21, G32, C33, C58, E44.

1 Introduction

The European banking sector has been grappling with increased systemic risk almost continuously since the outbreak of the global financial crisis. Episodes of turbulence include the public debt crisis, Brexit, the COVID-19 pandemic, and, more recently, the war in Ukraine. This turbulence has been straining banks' capital adequacy, stressing their solvency, sometimes leading to bank failures.

Various papers investigate the impact of the war in Ukraine on the macroeconomy and the spillovers that occurred in the financial (e.g. Boubaker et al., 2022; Izzeldin et al., 2023; Umar et al., 2022; Wu et al., 2023) and commodity markets (e.g. Gong & Xu, 2022; Kyriazis & Corbet, 2024; Lo et al., 2022). However, the research on its impact on the banking sector is significantly less numerous (Boubaker et al., 2023; Martins et al., 2023; Vu et al., 2023), and there are no studies analyzing the impact of the ongoing war on banks' capital adequacy. This paper fills the gap, additionally embedding the study in a comparative, longitudinal, and cross-sectional context that covers five distinct periods of systemic risk between 2010 and 2023, combining panel vector autoregression models (VAR) with quantile-based systemic risk measurement.

The paper contributes to the literature on systemic risk and the impact of crises on banks, building on, *inter alia,* Benoit et al. (2017), Anginer et al. (2018), Oordt and Zhou(2019), Li et al. (2020), and Batten et al. (2022). Despite the empirically confirmed knowledge that various economic and market indicators are relevant for bank stability, no study captures their impact on banks' capital position in a formalized framework combining panel studies with quantile-base risk measurement, possibly because the mentioned effects are nonlinear and intertwined in complex relationships.

Our paper adds to the existing literature by applying a dynamic panel study using the system generalized method of moments (SGMM) to formalize the relations between individual bank characteristics described by book-value indicators, the course and spillovers of systemic risk captured by a stock-market-based measure (ΔCoVaR) (cf. Adrian & Brunnermeier, 2016; Deng et al., 2023), and the exogenous country-specific characteristics. Autoregressive lagging effects and interactions included in the models allow us to capture the complex impact of a system of endo- and exogenous factors on the capital adequacy of systemically important European banks. Thus, our analysis improves the understanding of the effects systemic turbulence has on banks' capital adequacy, underpinning the larger market and macroeconomic factors that affect capital adequacy in the presence of systemic risk.

In total, we use about 270,700 unique data points related to 120 systemically important banks from 27 countries: 13 advanced markets and 14 emerging and frontier markets, including 26 European Union countries and the United Kingdom[1]. Panel analysis employs 40 endogenous and exogenous variables and is free from survivorship bias, which is crucial in systemic risk analysis. Our methodology, along with the sample size and study breadth, facilitates conclusions crucial for supervisory guidelines as it identifies the variables contributing to the decline in the capital position of systemically important banks when confronted with systemic risk. We also offer insights into the contrasts between the impact of systemic risk on capital adequacy in the previous

[1] Our study includes, additionally to the EU countries, also the UK which has been a member of the Union for a significant period of the time. For simplicity in the further parts of the paper we refer to all the banks in the study as „European" banks.

crises and the current one, which adds to the literature related to the impact of the Ukrainian war on the stability of the European banking sector.

Our results confirm that systemic risk captured by ΔCoVaR has a significant positive effect on the TCR in the periods leading to crises and a strong negative effect in the crisis aftermath. We capture this relationship in all turbulent periods, including the war in Ukraine. We further demonstrate that systemic risk modifies the impact of macroeconomic indicators on the capital position of banks, which may effectively turn the direction of this impact around. Specifically, any positive effects on the TCR of the GDP growth and current accounts balance dynamics weaken in the face of systemic risk – turning negative in high turbulence. Interestingly, the study confirms that a negative effect of the increasing public debt on the TCR becomes positive in the presence of systemic turbulence, which might be related to numerous liquidity and quantitative easing programs.

Regarding two larger-market indicators, we find that between 2010 and 2022, banks' ability to build robust capital did not strongly depend on the housing market dynamics, even when intertwined with a systemic crisis. In contrast, we confirm the effect of the US stock market on the TCR in all studied dimensions, including the crisis in 2022. This effect is strong and positive in calm periods and equally strong but negative when coupled with systemic turbulence. Thus, our results indicate the spillovers of systemic-risk-induced effects on the TCR between the US and Europe for both listed and unlisted banks.

The paper consists of three parts. First, we discuss the literature regarding systemic risk and its modeling challenges in emerging markets. Then, we discuss papers about the war in Ukraine and its impact on the economic environment and financial markets. The next part presents the hypotheses, methods, and empirical dataset. We present and discuss the results and conclusions in the third part of the paper.

2 Literature review

2.1 Systemic Risk and Contagion Effect

Systemic risk is the most intricate and multifaceted risk in finance and economics. It encompasses a multitude of aspects and has a ripple effect on the real economy. It differs from isolated failures in the financial system, instead representing a cascading reaction within the banking sector triggered by interconnections in the financial system. Furthermore, systemic risk is closely intertwined with interbank market liquidity, banks' resilience to external and internal shocks, and the transmission of risk among systemically significant institutions, a phenomenon known as contagion (cf. Silva et al., 2017). This risk evolves over time due to mechanisms of accumulation and amplification resulting from mutual reinforcement and feedback effects (cf. Benoit et al., 2017). It can also be perceived as the product of the individual tail risk of the bank and its linkages with the financial system (Oordt & Zhou, 2019).

The intersection of these processes and characteristics affects, inter alia, the capital adequacy of systemically important banks. Empirical evidence suggests that solvency and liquidity drop during such episodes, and some banks fail, while the impact extends beyond the banking sector, affecting the real economy. These mechanisms underscore the significance of contagion as an integral component of systemic risk (Silva et al., 2017) stemming from the interdependencies among participants in the financial system. Consequently, contagion extends the risk faced by individual banks (micro-level instabilities), giving it an amplified and system-wide dimension (systemic risk). Yet another amplifying factor in these processes is the autoregressive character of the capital adequacy itself – where a weaker capital position makes banks more prone to shocks (Anginer et al., 2018), weakening their capital adequacy even further.

Interconnections, correlations, and contagion were found to be fundamental elements of systemic risk in all turbulent periods from the global financial crisis up to the COVID-19 pandemic (Acemoglu et al., 2015; Andrieş et al., 2020; Batten et al., 2022; Benoit et al., 2017; Brownlees & Engle, 2017; Li et al., 2020; Markose et al., 2012; Rizwan et al., 2020). The most thoroughly investigated channels of systemic risk that affect the capital adequacy of financial institutions include liquidity, information, and balance sheet channels, especially mutual exposures to credit risk and the structural channel, which relates to high concentrations and market fragmentation (Chen & Duffie, 2021; Pala, 2022). Indeed, research findings indicate that overly dense interconnections (Anand et al., 2013; Naghavi & Lau, 2014) and poorly structured networks (Babus, 2016; Babus & Hu, 2017; Elliott et al., 2014; Farboodi, 2021; Markose et al., 2012) serve as mechanisms for the propagation of shocks.

That said, the majority of empirical research does not cover a sizable portion of the European system, mainly due to data availability constraints related to legal restrictions, the specific nature of small local exchanges, and the limited range of financial instruments traded there.

2.2 Challenges to Measuring Systemic Risk in Emerging Markets in Europe

Due to all the spillover and contagion effects of systemic risk described earlier, it is impossible to properly analyze European systemic risk without considering its emerging markets. However, such an analysis is challenging for several reasons.

A vital factor affecting systemic risk in Emerging Markets in Europe (EMEs) is the foreign ownership of their banking sector, with over 90% of banking assets in many countries in the region held by foreign owners (Radulescu et al., 2018, pp. 7–8). Consequently, foreign-owned banks are the primary source of credit in European emerging countries (Dumicic, 2018, p. 2). This poses a substantial macroprudential challenge. Despite EMEs' early use of various macroprudential tools, most subsidiaries of large Western European banks found ways to evade regulations thanks to their relationships with parent institutions, increasing systemic risk in the region.

Jočienė (2015) and Barkauskaite et al. (2018) discuss the importance of foreign parents' influence on the strategic and tactical decisions of smaller systemically important European banks and its negative effects on their resilience to shocks. An illustrative example is the rapid deleveraging of foreign-owned Romanian and Bulgarian banks, impacting credit supply to the real economy in the Balkans (Radulescu et al., 2018). Capital ratios (TCRs) of parent banks (not daughter banks) played a role in this process. Despite local regulatory efforts, these processes could not be halted.

Despite the multitude of systemic risk measures (for reviews, see, e.g., Bisias et al., 2012; Silva et al., 2017), only a handful of studies present applications of comprehensive systemic risk measures to EMEs. Several methods use broader market indices (Hollo et al., 2012; Jakubík & Slacík, 2013; Kubinschi & Barnea, 2016) that do not permit individual bank analysis essential for macroprudential financial market regulation. Quantile-based systemic risk measures are also rarely applied. Additionally, data limitations and the scope of these analyses, covering no more than 25% of all existing systemically important European banks (Karas & Szczepaniak, 2021), reduce the effectiveness of these studies, leaving a research gap to be filled. To mitigate this issue, we construct a wide European financial system model to estimate ΔCoVaR.

This approach makes the studied financial system more complete while maintaining coherence. Its additional advantage is capturing a significant source of systemic risk amplification mechanisms, namely that European exchange markets are intricately connected, creating strong contagion channels between the Western and Eastern markets. Accounting for these contagion effects changes the analysis landscape for the CEE region.

2.3 The Impact of the War in Ukraine on the Banking Sector and Shock Propagation

The influence of war on financial markets, especially on stock exchanges, has been observed since World War II. Recent years have confirmed these observations: numerous studies demonstrated that the war in Ukraine affects prices in currency markets (Aliu et al., 2023; Chortane & Pandey, 2022; Hachicha, 2023; Sokhanvar et al., 2023), commodity markets (Adekoya et al., 2022; Aliu et al., 2023; Antonakakis et al., 2017; Fang & Shao, 2022; Gong & Xu, 2022; Lo et al., 2022) and traditional stock exchanges (Anyikwa & Phiri, 2023a, 2023b; Umar et al., 2022; Wu et al., 2023), increasing risk and volatility. This applies to markets in the conflict-affected countries, as seen with Ukraine and Russia (Lyócsa & Plíhal, 2022), and to distant markets.

Studies show that the impact extends not only to European markets (Ahmed et al., 2023; Kumari et al., 2023) but also reaches countries like India (Pandey et al., 2023) or even Australia (Kamal et al., 2023). Notably, this impact appears more pronounced in developing countries. Multiple studies also indicate that risk shocks resulting from the war spread to global markets (Boubaker et al., 2022; Izzeldin et al., 2023; Sun & Zhang, 2023; Umar et al., 2022).

The effects of war transmitted through various financial markets can be highly significant for banks' financial condition and stability due to their substantial investment and financing exposure. The significance of such transmission channels for the banking sector has been confirmed in the case of shocks related to other recent financial crises (Batten et al., 2022), while Boubaker et al. (2023) and Martins et al. (2023) confirm such effects for the war in Ukraine.

Geopolitical conflict is a particular source of systemic risk because it strongly impacts economic factors. The macroeconomic effects of the war in Ukraine and its influence on the economy have not yet been fully explored due to the delays in economic factors' response to shocks. However, current indicators related to inflation or GDP growth leave no doubt that the war in Ukraine affects these variables, as was the case with previous wars, especially in countries close to the conflict (Carmignani & Kler, 2018; Oja, 2015; Vasylieva et al., 2018).

The stronger impact on banks in Europe can result from uncertainty (Athari, 2021; Eksi & Onur Tas, 2022; Talavera et al., 2012) and the conservative attitudes of households and firms, leading to reduced investment (Bougias et al., 2022; Mattera & Soto, 2023; Shmygel & Hoesli, 2023). Equally important is the influence of geopolitical factors on borrowers' functioning and financial condition (Abbassi et al., 2023; Mattera & Soto, 2023). The war's impact on agricultural product prices also plays a role (Saâdaoui et al., 2022; Von Cramon-Taubadel, 2022). The same applies to the effect on global fuel prices (Adekoya et al., 2022; Fang & Shao, 2022; Gong & Xu, 2022; Kočenda & Moravcová, 2024; Kyriazis & Corbet, 2024; Lo et al., 2022). Businesses are also affected by disruptions in supply chains (Steinbach, 2023) and significant upheavals in trade relationships (Estrada & Koutronas, 2022; Kancs, 2023). Lastly, sanctions adversely impact not only Russia (Allen, 2022; Sedrakyan, 2022) but also European countries (Crozet & Hinz, 2020).

All the factors discussed above have the potential to influence the capital adequacy of European banks. However, the extent of these effects is not obvious and requires further examination. The strength of these effects depends on various global and country-specific factors and specific bank characteristics.

3 Data and Research Methods

3.1 Systemic Risk and Contagion – ΔCoVaR Model

Categorizing the outcomes of systemic risk as infrequent events with significant losses appears apt because their likelihood is low (Glasserman & Young, 2015), yet the resulting losses can be exceptionally substantial (Biais et al., 2016; Kobayashi, 2013) since they accumulate on a systemic scale. Thus, the consequences of systemic risk manifesting as financial losses manifest in the left-low quantile of the return distribution. At the same time, quantile-based measures of systemic risk, which examine the concurrent occurrence of losses induced by shocks, are suitable for identifying contagion effects within the systemic risk process because contagion can be identified by monitoring the evolving correlations in the returns on equity of these banks over time (Acharya & Rajan, 2022; Acharya, 2009; Adrian & Brunnermeier, 2016; Brownlees & Engle, 2017). For these reasons, we choose to apply the ΔCoVaR model to measure European systemic risk.

ΔCoVaR is a conditional quantile-based risk measure drawing from the concept of Value at Risk (VaR) that captures the condition and the interconnectedness of the banking sector, indicating how the banking sector index decreases when the stock price of an individual bank falls, conditionally on systemic triggers (losses at least at the VaR level). As such, this measure focuses on risk transmission between banks in response to an external shock. Therefore, a bank's ΔCoVaR represents its potential for risk propagation.

In its original form, ΔCoVaR is calculated on a country-based level. That means that the banking system s of a given country is defined as a portfolio of N systemically important banks in that country, where each bank i is characterized by a weight w_i. Typically, the weights of banks in the system are based on their size and proxied by capitalization (Adrian & Brunnermeier, 2016). Due to data limitations, this method excludes several smaller and less developed European countries from the analysis.

To overcome this matter, we construct a European banking system defined as a portfolio of N systemically important banks in the European Union and the UK. Banks that constitute each system s in the study have been recognized by the relevant (national and European) financial market supervision authorities as systemically important (O-SII) (Bank of England, 2023; European Banking Authority, 2023) whose average systemic importance score (SIS) in the study period was at least 275 points, i.e., above the systemicness threshold (cf. European Banking Authority, 2014; Directive 2013/36/EU).

In such an approach, it would be counterproductive to base the weights on capitalization, as different stock exchanges in Europe have very different sizes. Therefore, capitalization is not an objective proxy for systemic relevance. Thus, we base each bank's weight w_i on its Systemic Importance Score representing its actual contribution to risk in the European system s. This generalization is possible as all SIS scores are comparable: calculated according to the same EBA methodology and expressed on the same universal scale.

The rate of return from quotations on the stock exchange at time t for bank i is denoted as $r_{i,t}$, and for the European system s as $r_{s,t}$. In this context, we assume that:

$$r_{s,t} = \sum_{i=1}^{N} w_{i,t} \cdot r_{i,t}, \qquad w_{i,t} = \frac{c_{i,t}}{\sum_{j=1}^{N} c_{j,t}}, \qquad (1, 2)$$

where $w_{i,t}$ is the weight of a systemically important bank i in system s, representing the share of the importance indicator $c_{i,t}$ based on its Systemic Importance Score (SIS) (EBA, 2023) from the country of its main exchange listing.

The adopted assumption, expressed by Formula (1), is a direct application of the classical portfolio optimization theory. For coherence, we use the same approach for calculating total systemic risk using the CoVaR measure (Formula (6)).

The proposed method allows for estimating the ΔCoVaR measure for a range of banks, for which the traditional approach based on capitalization makes it impossible. Moreover, it better captures the contagion effect generated in the European Union's banking sector by eliminating the subdivision of the dataset into smaller (national) subsets. Furthermore, it enables capturing the "actual systemic importance" of each bank (Directive 2013/36/EU, art. 97, para. 4), basing its weight on the SIS indicator rather than just the size, as in the original method.

As a result, we assume that the value at risk (VaR) of each bank i in the system s, for a confidence level of $1 - q$, is equal to:

$$VaR_{i,t}^{q}(r_{i,t}) = \inf \{r_{i,t}: F_{i,t}(r_{i,t}) \geq q\}, \qquad (3)$$

where $F_{i,t}$ is the distribution function of $r_{i,t}$, i.e., $VaR_{i,t}^{q}(r_{i,t})$ is the q-quantile of the distribution $F_{i,t}$. Additionally, we assume that the return distributions of banks belong to a family of distributions with time-varying dispersion.

$CoVaR_{s,t}$ of the banking system s corresponds to the value at risk $VaR_{s,t}$ of the return rate from the market obtained conditionally on bank i realizing a loss at the level of $VaR_{i,t}$, where q constitutes:

$$q = \mathbb{P}\left(r_{s,t} \leq CoVaR_{s,t}^{q|r_{i,t}<VaR_{i,t}^{q}} \middle| r_{i,t} < VaR_{i,t}^{q}\right). \qquad (4)$$

$\Delta CoVaR_{i,t}$ allows measuring the marginal contribution of each bank to the overall systemic risk, capturing it in a non-causal sense. We define the stress threshold of bank i, i.e., the shock, as $VaR_{i,t}^{q}$, and the shock itself occurs whenever losses are at least at the level of $VaR_{i,t}^{q}$.

$$\Delta CoVaR_{i,t}^{q} = CoVaR_{s,t}^{q|r_{i,t}<VaR_{i,t}^{q}} - CoVaR_{s,t}^{q|r_{i,t}=Median(r_{i,t})}. \qquad (5)$$

To build time series covering the entire system, reflecting the contagion effect captured by the ΔCoVaR of individual banks, the portfolio aggregation method was again used on a predefined set of systemically important financial institutions $i \in \{1, 2, \dots, N\}$.

$$\Delta CoVaR_{s,t}^{q} = \sum_{i=1}^{N} (\Delta CoVaR_{i,t}^{q} \cdot w_{i,t}). \qquad (6)$$

The aggregation proceeds by applying the weight resulting from the SIS indicator of each systemic bank i (O-SII) and its ΔCoVaR measure, analogously to Formulas (1) and (2)).

We use the GJR-GARCH model to estimate conditional volatility parameters and the GARCH-DCC model for estimating the (conditional) time-varying correlation (cf. Benoit et al., 2017). We use the R environment (Galanos, 2022; R Core Team, 2021) for calculations.

3.2 Panel Models – SGMM

To conduct panel analysis, we apply the system Generalized Method of Moments (SGMM), developed by Blundell and Bond (1998), as the collected panel data (variables described in Tables 1-4) facilitates the analysis in both cross-sectional and temporal dimensions. The selected assumption-flexible estimation method SGMM is particularly advantageous for this study because endogenous explanatory variables are a vital component of our analysis. This is related to the fact that feedback and autoregressive effects are typical for systemic risk materialization.

As Bond (2002) highlights, SGMM is especially valuable when dealing with autocorrelation or heteroskedasticity, ensuring unbiased and precise outcomes. In contrast to static panel models, GMM accommodates lagged observations of the dependent variable, eliminating the need for the strict assumption about the exogeneity of independent variables, which would be unrealistic for this study. Andreß et al. (2013) confirm that the described flexibility is notably beneficial for studies of the banking sector.

The final functional form of the applied dynamic model is as follows:

$$TCR_{i,t} = a_1 TCR_{i,t-1} + a_2 EX.VAR_{i,\tau} + a_3 MACROECON.VAR_{i,t} + a_4 BANK.VAR_{i,t} + v_{i,t} + const\ , \tag{8}$$

where $TCR_{i,t}$ represents the dependent variables, is $EX.VAR_{i,\tau}$ the vector of experimental variables, including the interactive variables in period $\tau = t$ or $\tau = t-1$; $MACROECON.VAR_{i,t}$ is the vector of macroeconomic variables in period t; $BANK.VAR_{i,t}$ is the vector of unit-specific variables characterizing the specific operation of a given bank in period t; $v_{i,t}$ is the random component that is the sum of a time-constant individual effect and a pure random error $\varepsilon_{i,t}$.

Panel analysis applies a large set of independent and experimental variables, including twenty interactive ones, described in Sections 3.3 and 4.2. To assess the significance of the variables in the models in the presence of random component heteroskedasticity, we apply a one-step estimation, following the suggestion of Blundell and Bond (1998). We use the Arellano-Bond autocorrelation tests for first and second-order differences and the Hansen test to evaluate model significance.

3.3 Data

The study covers the period from 2010 to 2023, including four turbulent periods: the European public debt crisis, Brexit, the coronavirus pandemic, and the armed conflict in Ukraine. The sample encompasses 120 banks from 27 European countries, including 13 developed and 14 developing (emerging and frontier) ones. The study encompasses 26 European Union countries and the UK. Therefore, the study includes about 74% of all systemically important financial institutions in the studied countries with an average systemic importance score of at least 275 points (cf. Bank of England, 2023; European Banking Authority, 2023). Given the purpose of the study and its focus on commercial banks, it is worth mentioning that the sample includes not less than approximately 88% of the commercial banks considered systemically important in the studied countries. We present the table listing the banks included in the analysis and their systemic importance scores in the Online Appendix.

We apply three data tiers for panel analysis – bank-level, banking sector-level, and country-level. Altogether, we use about 249,200 stock market data entries, as well as approximately 21,500 book-value and aggregated country-level data entries, on which we base 40 variables used in the panel analysis. The variables include eleven control variables, among them an autoregressive TCR variable (Table 2); 29 experimental variables, including nine basic experimental variables and 20 interactive ones (Table 1); and one dependent variable, i.e., the TCR. Among the experimental variables, twelve were constructed to conduct one of the dimensions of the robustness analysis (see Section 4.4). Tables 1 and 2 present the description of the analyzed variables, Table 3 presents the descriptive statistics of the research sample, and Table 4 captures their correlation matrix.

[Insert Tables 1 - 4 here]

We use multiple data sources to mitigate various data limitations discussed in the earlier sections. Bank-specific accounting data were obtained from the BankFocus database (2023), stock market data were collected from the Refinitiv Eikon (Thomson Reuters) database (2023), and aggregated country-level data were obtained from the International Monetary Fund database (2023), the World Bank (2023) and European Mortgage Federation (2021, 2023). Systemic Importance Scores were taken from the document repository of the European Systemic Risk Board (2023). Such diverse data sources enable a comprehensive scope for the analysis.

4 Empirical results

4.1 Research hypotheses

In the first step of the study, we estimate the time series of the ΔCoVaR model for the European banking sector and each studied bank. This model captures two crucial aspects of systemic risk that affect banks' exposure to systemic risk triggers. It combines the information about tail risk materialized for a given day in each bank with the changing correlation of tail risk across all banks in the given financial system, signifying the strength of risk transmission (spillover) across the system. By applying ΔCoVaR, we capture the mixture of endo- and exogenous aspects of systemic risk that, based on the literature, are expected to adversely affect the capital adequacy of the banks in the sample. Thus, we formulate the first hypothesis:

H1: Systemic risk systematically adversely affects the capital adequacy of systemically important banks in the European Union and the UK.

To verify this hypothesis, we estimate the systemic risk effect using a set of interactive variables that describe the potential channels that transmit and/or amplify the impact of systemic risk estimated via ΔCoVaR measure onto systemically important banks' Total Capital Ratios. Based on the literature review discussed in Section 2.1, which indicates that systemic risk negatively impacts the financial stability of systemic banks, we expect to confirm Hypothesis 1 in our empirical analysis. Given the specificity of the risk factors that drive bank fragility detailed in Section 2.1 and the studies cited in Table 2, we must control a large set of bank-specific and country-specific characteristics in the process. Therefore, we introduce a substantial set of endo- and exogenous control variables.

A separate issue that requires investigation is whether the phenomena characteristic of the previous crises, which were typically financial and much less localized than the war in Ukraine, are also typical for the current crisis. Thus, we formulate a complementary hypothesis:

H2: Systemic risk accompanying the war in Ukraine adversely affects the capital adequacy of systemically important banks in the European Union and the UK.

To verify Hypothesis 2, we replicate the analysis applied to Hypothesis 1, employing a binary variable that denotes the presence or absence of the war. Given the uniqueness of the current crisis and the lack of literature investigating this specific issue, we do not form any ex-ante expectations regarding the second hypothesis.

4.2 Systemic spillovers in the study period

The results plotted in Figures 1 and 2 present the course of systemic risk captured by ΔCoVaR estimations for the European Union-wide banking sector and the banking sectors of the 27 countries in the sample. In several periods, individual banks' conditional value at risk increases significantly, and this is coupled with the dynamically increasing correlation of losses that point to bigger risk spillovers. These effects translate to four periods of increased systemic risk, followed by a series of smaller risk peaks (echoes) of the main turbulence.

[insert Figure 1 here]

Among the four turbulent periods, the first is the public debt crisis in Southern Europe coupled with the series of LIBOR-rate-related scandals in Western Europe. This crisis spreads across the longest period, between 2011 and 2014, affecting different banks at different times, with a country-specific impact. The initial impact is visible mostly in the UK and can be traced back to the LIBOR-rate manipulations and the related scandals. In contrast, the highest impact relates to Greek and Cyprian banks, corresponding to the scale of the public debt crisis materialization in that geographical area.

The next turbulent period stretches around the decision of the UK to exit the European Union. However, in this case, the initial shock (coinciding with the referendum results) and the following aftershocks affect only about half of the analyzed banks, especially in the UK, Ireland, and Malta, but also in France, Spain, Italy, and Slovenia. A clear correspondence between the shock transmission and the banking sector's ownership structure is noticeable here.

The biggest captured peak of ΔCoVaR of the European banking sector relates to the COVID-19 pandemic. Moreover, in this instance, the risk increases most suddenly – almost vertically. It happens across one month for the vast majority of the analyzed banks. Additionally, the size of the impact of this turbulence is considerable and most comparably high among all the studied banks. In effect, the system-wide CoVaR records the highest levels of systemic risk, as presented in Figure 2. Importantly, this risk also subsides more smoothly compared to other studied turbulent periods.

[insert Figure 2 here]

The final turbulent analyzed period starts in early 2022, right around the first open military attack of Russia against Ukraine, marking the start of the war. This crisis begins less suddenly than the previous one, with pre-turbulence signals recorded in several CEE countries in December 2021. The turbulence increase in the early months of 2022 is followed by echoes typical for systemic risk (aftershocks) later in summer and in 2023, all across Europe. As expected, the banks in the countries neighboring the conflict, such as the Baltics, Poland, or Romania, record higher shocks and stronger aftershocks. Still, the turbulence is noticeable across all the analyzed countries and results in elevated levels of the European ΔCoVaR measure as well.

4.3 Panel analysis

In the second step of the study, we apply panel analysis to investigate the impact of systemic risk on the capital adequacy of systemically important banks. Here, we construct the systemic risk variable based on the course of ΔCoVaR estimations. Nonetheless, to allow for further meaningful conclusions, we investigate the mechanisms through which systemic risk impacts capital adequacy. We formalize captured relations with interactive variables, modeling the interactions between the larger-market and macroeconomic variables and banks' capital adequacy (expressed via Total Capital Ratio, TCR) in the presence of the changing levels of systemic risk.

Interactive variables are especially useful in studying multidimensional, complex phenomena. For this reason, they are well-suited for systemic risk analysis. They enable the adaptation of the VAR models to capture the impact of selected explanatory variables on the TCR while controlling for other factors and simultaneously analyzing how these variables interact to influence the phenomenon under study. By introducing interactions, one may observe the effect of one explanatory variable as mediated by another, instantaneously testing many hypotheses and exploring various aspects of the studied effects. In the case of this study, using interactive variables, it is possible to observe which variables significantly affect the banking sector and whether the presence of systemic risk modifies this impact. Additionally, using a binary interactive variable allows us to assess how these relationships change in the presence of a military conflict.

Based on the literature findings (Dermine, 1985; Kashyap & Stein, 1995; Kubinschi & Barnea, 2016; Reinhart & Rogoff, 2009; Rousseau & Yilmazkuday, 2009; Shkolnyk & Koilo, 2018), we base the interactive variables on five different indicators. Three are macroeconomic and capture the effects of the GDP dynamics, public debt burden, and current accounts balance position. The remaining two are market indicators that capture the price effects in the stock exchange and the housing market.

Constructing interactive variables requires *a priori* modifications of the applied wider-market indicators to capture the dynamics between said indicators and systemic risk reported in the abovementioned literature. Additionally, the variables need an objective scale to be comparable across a large sample of countries and markets with different sizes and economic development levels. In response to such a challenge, we construct the proposed variables based not directly on the levels of the indicators but on a more elaborate basis, such as, e.g., dynamics of change or quantile of loss. We present the specifics regarding the construction of these variables in Table 1.

To start with, we include all the control macroeconomic and bank variables reported in the literature in the regression. These variables include a set of bank-specific variables (size, profitability and efficiency, liquidity, balance sheet structure) and an autoregressive variable, namely the values of the TCR from the previous year. Moreover, we include two country-specific macroeconomic variables – inflation (CPI) and unemployment (UN). The variables and the indications of previous studies that apply them are presented in Table 2. We also include five variables based on the larger-market country-specific indicators in their non-interactive form: the real GDP growth per capita, the ratio of the general government gross debt to GDP, the annual pp. change of the current account balance to GDP ratio, the annual pp. change in the real housing prices, and the 0.05-quantile of the daily returns on the S&P500 index within each year. We introduce these results next.

[insert Table 5 here]

Among the eleven independent variables indicated in the literature as potentially significant for the presented panel, we confirm that only six affect the TCR of systemic banks significantly in our sample in at least one Model (cf. Models 1-7, Table 5). Among them, there are two macroeconomic variables (inflation and unemployment) and several bank-specific characteristics related to banks' size (logarithm of total assets, loans (loans growth, loans to total assets), and funding gap (liquid assets to total assets and short-term funding). Interestingly, we find such variables as net interest margin, non-interest income to operating revenues, cost to income, or loans to deposits – to be consistently statistically insignificant (both in the baseline and robustness models). As expected, we confirm that the TCR depends, *inter alia*, on its own value from the previous year (TCR (-1)).

Next, we add the experimental variable constructed based on ΔCoVaR (EX_SYS). As presented in Table 5, Model 2 is inconclusive, as the experimental variable presents a *p*-value of 10,34%, close to the borderline significance. We confirm the results with a series of robustness checks by applying different variable combinations. The results reconfirm the observation that the EX_SYS variable is indeed statistically significant. Furthermore, when we limit the number of variables to the robustly significant ones, the strength of the captured relationships increases, as confirmed in Models 4 and 8 with the decreased *p*-value, corroborating the results.

Surprisingly, the systemic risk variable has a positive relationship with the TCR, contrary to the expectation formulated in Hypothesis 1. At first glance, such a result seems counterintuitive. However, one must consider that the EX_SYS variable provides a contemporaneous context to systemic turbulence because the panel models predominantly use book value data that is available only on a yearly scale. Thus, the EX_SYS variable also captures the growth effects that preceded the crises (e.g., bubble build-ups, cf. Brunnermeier & Oehmke, 2013) and only partially the crisis aftermath with its detrimental effects. All the subsequent models in which we apply the EX_SYS_1 variable, i.e., the systemic risk variable lagged by one period (one year), confirm this interpretation. The lagged systemic risk variable has a negative sign, capturing the aftermath of each financial crisis and indicating a negative relationship with the TCR (Models 5 and 9).

These initial results are indicative of a corroboration for Hypothesis 1. Nevertheless, further analysis is necessary, given the complexity of the channels through which systemic risk may be affecting the capital position of systemically important banks.

It is also important to point out that four out of five variables constructed based on the larger indicators from the literature are insignificant for the TCR of the banks in the sample (Models 1, 2, and 6). Such a finding stands in line with the literature. Indeed, the literature review in Section 2.1 suggests that larger-market indicators may be significant for banks only when systemic turbulence manifests. Thus, to further corroborate the initial findings that confirm Hypothesis 1, the literature indications prompt the necessity to introduce the interaction between systemic risk and said variables to capture the underlying processes better.

4.3.1 Interactive variables

Based on the analysis discussed in Section 4.2 and a series of robustness tests mentioned earlier and further described in Section 4.3, in the final part of the study, we perform the analysis on two types of models: larger models (with all the control variables) and the smaller ones, where we limit the list of control variables only to those that were consistently statistically significant in the larger panels. To further ensure the robustness of our results, we keep the lagged EX_SYS variable in the equation to verify that the effects captured by the experimental interactive variables bring additional information into the model on top of the systemic risk variable itself. The additional benefit of this solution is its ability to capture non-linear relations that are likely to partake in the studied processes.

We provide two perspectives in this part of the study. Firstly, we consider the interactions in the whole study horizon, including all turbulent periods of increased systemic risk. In this view, we analyze the data for generalizable, systematic relations between the studied interactive variables and the TCR of systemically important banks. This part of the analysis addresses Hypothesis 1.

The second perspective focuses on studying the interactive variables only in the context of 2022 turbulence, i.e., concerning systemic risk related to the war in Ukraine coupled with increased inflation in Europe. To reach this goal, we reconstruct the interactive variables in a binary way so that they take the value of zero in 2010-2021 and the value of the interaction between the wider-market indicator and systemic risk in 2022. It permits inferring if the relations identified as systematic in the whole sample are the same for 2022 or – if they are different and what the differences are. This way, we can compare the recent systemic risk episode with the other turbulent periods. This part of the analysis addresses Hypothesis 2.

The interactive variables discussed first refer to the effects brought about by the interaction between three macroeconomic indicators and systemic risk. They refer to public debt, GDP growth, and current accounts balance. We discuss the results per variable as follows. In all models, systemic risk variables have a consistent direction of impact on the TCR, with a positive effect before the crisis and a negative effect afterward. Interactive variables give more divergent results.

The debt-to-GDP ratio shows an interesting pattern (Models 10-13). It is negatively related to the TCR in all the studied configurations (see also Models 30-33), showing that banks in countries with higher and growing public debt tend to have a weaker capital base. This is an intuitive finding, especially given the nature of the public debt crisis and the COVID-19 pandemic, as well as previous studies' results. However, when we intersect the public debt dynamics with systemic turbulence, we record a positive relationship between the TCR and the level of debt. Although peculiar at first glance, this observation reflects the bailouts, quantitative easing, and direct liquidity provisions for financial institutions and other firms around turbulent periods. Such interpretation aligns with the fact that these effects are also recorded for the binary variable, suggesting that the rescue packages' impact was still at work in 2022 (cf. European Central Bank, 2023). Thus, our results suggest that the ongoing military crisis does not seem to wipe out these liquidity-injection-related effects.

[insert Table 6 here]

Concerning the second macroeconomic variable, the growth of the GDP per capita (Models 14-17), we are not able to confirm any significant effects on the TCR similar to the ones reported in the literature (Miklaszewska & Kil, 2023; Tan, 2016; Vu et al., 2023). However, the results related to the interactive variable show that in the periods of substantially increased systemic risk, a strong, robust negative relationship exists – pointing to a dampening effect systemic risk has on the relationship between economic growth and the financial condition of banks reported in other studies. Our results show that any significant positive effects reverse in the face of systemic risk manifestation.

[insert Table 7 here]

Importantly, when isolated for 2022, such effects are not statistically significant at <10%. Therefore, the above conclusion does not hold for the war in Ukraine. Thus, there may be a specific difference between the current and the previous crises. However, a more likely possibility is that these effects have not fully materialized yet. In essence, the macroeconomic effects, especially the ones related to GDP growth, affect the banking sector with a lag of up to three years (Reinhart & Rogoff, 2009). This explanation seems more plausible given that the larger Models 35 and 37 (robustness) capture this effect as borderline significant. It is also in line with a common conclusion about the lagging impact of GDP growth on financial stability presented in various financial stability reports (e.g., European Central Bank, 2023). Overall, the analysis must encompass a longer period before final conclusions regarding this effect may be drawn. Such data is currently unavailable, as the crisis studied is still very young.

[insert Table 8 here]

The results related to the interactive variable based on the dynamics of the current accounts balance (CAB) (Models 18-21) show a similar pattern as those related to GDP growth, but the effects appear stronger and much more consistent. This aligns with the economic theory and the aforementioned publications, reporting that this macroeconomic indicator is characterized by shorter lags when considering its impact on financial stability (European Central Bank, 2023; Reinhart & Rogoff, 2009). When analyzed outside of the interaction with systemic risk, the CAB dynamic positively relates to the TCR, indicating that banks tend to strengthen their capital position when the deficit is smaller. Yet, when systemic risk increases, this effect dissipates. In fact, we record a negative relationship for the interactive variable, meaning that systemic turbulence reverses this effect. Interestingly, the detected relations for the war in Ukraine are just as substantial – indicating a particularly fast impact of the studied factor in the presence of systemic risk. These results are robust (cf. Models 38-41).

The last group of interactive variables captures the impact of the stock and housing markets on banks. These variables aim to capture the dynamic impact of losses, so they were based on the return rates and the changes in the 5% quantile (left tail) of returns rates' distribution.

[insert Table 9 here]

According to our results, the housing market price dynamics did not robustly affect commercial banks' TCRs in the study period, even when intertwined with a systemic crisis (Models 22-25 and 42-45). In all the models, except for Model 45 (significance at 10%), the studied variable presents *p*-values between 0,1 and 0,13. This indicates that the effect, although potentially consistent, is very weak. It suggests that commercial systemically important European banks rather effectively manage the changing housing price trends. Such an effect is consistent for all the turbulent periods under investigation, including the crisis in 2022. Since the analyzed period does not include the global financial crisis, our study implies that the importance of this particular risk factor decreased after 2009 and the macroprudential reforms that came afterward[2].

The last variable included in this analysis relates to the stock market (Models 26-29). Since the CoVaR-based EX_SYS variables are stock-market-based, we constructed the stock market indicator on the S&P500 to make our analysis robust. In contrast, all CoVaR estimations were based on European stock exchanges only (Formulas 1-6).

[insert Table 10 here]

Investigating if the losses on the US stock market significantly affect the TCR of European banks, we find a long-term positive relationship showing that the growing US stock market helps banks strengthen their capital positions[3]. This effect reverses in the crisis, indicating that the losses that follow bubble bursts in the crisis

[2] This conclusion is limited to commercial banks and to the period 2010-2022. The results obtained for mortgage banks and investment banks (not reported here - beyond the paper's scope), as well as studies that capture the global financial crisis, show opposite results.

[3] The effect is not captured for the ΔCoVaR constructed according to the method proposed by Adrian and Brunnermeier (2016) in which we use a limited number of institutions due to data limitations imposed by the original calculation approach. These results further highlight the betterness of the proposed alternative CoVaR construction.

aftermath weaken banks' TCRs. The significance of this interactive relation is weaker for the year 2022 than for the whole study period. Still, the crisis related to the war in Ukraine has not ended, and its full scale is yet unknown.

The results confirm the spillovers between the American and European stock markets reported in the literature discussed in Sections 2.1 and 2.2. We also confirm that the effects become stronger in turbulent periods as captured by the interactive variables that depict systemic risk multiplied by stock market losses. Our results, confirmed by various robustness checks (*inter alia* Models 46-49), confirm that the American stock market has a statistically significant effect on the TCR of European systemic banks, including the not listed ones comprising about half of the study sample.

The models presented in Table 10 capture one other interesting effect concerning the basic (non-interactive) systemic risk variables. Depending on whether the European-system-wide CoVaR is used or the traditional one, we see the significance of the lagged systemic risk effect or the contemporaneous one. It shows that the system-wide ΔCoVaR proposed in this paper captures the lasting negative effects better, while ΔCoVaR constructed based on the original approach better depicts the instantaneous systemic risk effects. On the other hand, regarding the interaction between the US stock market losses and systemic risk and its impact on the TCR of banks, both CoVaR estimation methods generate similar, robust, and statistically significant results.

In conclusion, the results confirm – in relation to both hypotheses, that systemic risk significantly affects the TCR in the studied panel of banks. Experimental variables are systematically significant in the whole study period and the war-depicting binary scenario. The fact that in all the panels, either the EX_SYS variable, the lagged EX_SYS_1 variable, or both are significant, even when we include the interactive variables, confirms that the systemic risk-induced effects are non-linear and complex, and they likely work in a feedback-loop setting.

The results show that systemic risk induces stronger effects of the macroeconomic and wider-market variables on the TCR, and when we consider the aftermath of systemic risk materialization, such risk negates or even reverses the positive effects reported in previous studies. Furthermore, we conclude that systemic risk affects the TCR adversely only when considered either with a lag or in an interaction. This confirms the nonlinear and complex impact of systemic risk on the capital position of systemically important banks, where in the short-term, this risk may create an environment where banks increase their capital base (during the hypes that precede the bubble bursts) but, in the horizon longer than one year, this risk significantly adversely affects their total capital ratios.

4.4 Description of the robustness analysis

As explained in Section 3, we apply carefully selected estimation methods that are well-suited for working with the data and the phenomena analyzed in this paper. Nonetheless, we also conduct robustness analysis in two additional dimensions. The first relates to the estimations of systemic risk, while the second refers to the robustness and stability of the presented panel regression results. Combined, these two dimensions of robustness analysis confirm the robustness of the conclusions drawn regarding Hypotheses 1 and 2.

We propose innovations in ΔCoVaR estimation that are described in Section 3.1. These innovations improve the precision of the systemic risk time series. Nonetheless, for robustness, we also estimate ΔCoVaR following the methods proposed in the literature (Adrian & Brunnermeier, 2016; Benoit et al., 2017). In this approach, instead of constructing a European-Union-wide cross-border financial system, we construct a series of nationally defined financial systems, where each such system is a set of Systemically Important Financial Institutions. As before, following the EBA's definition, these are O-SIIs characterized by a SIS score of 250 or more. To obtain the European course of systemic risk, we take each daily median observation from across all the national systems. Based on the series of such daily observations, we construct the ΔCoVaR for Europe.

This approach eliminates from the analysis all the countries that have less than two systemically important banks listed on their national stock exchanges. In effect, the panel variables based on the so obtained ΔCoVaR measure (EX_SYS_R and EX_SYS_1_R) are based on 55 banks from only 16 countries (Belgium, Bulgaria, Estonia, Finland, Norway, Hungary, Lithuania, Latvia and Slovenia must be omitted in the estimations). In the next step of the robustness analysis, we replicate all the panel analyses conducted using the baseline variables EX_SYS and EX_SYS_1. We present these models (no 28-49) together with the baseline models in Tables 6-10.

We conduct a battery of additional tests to verify the robustness of the panel regressions. To check the robustness of the panel studies we repeat all the models using different combinations of control variables. The main results, i.e., the smallest models, with only these control variables which were statistically significant in the full panel (Model 1, Table 5), are accompanied by the results obtained for the largest panels that include all the control variables applied in the study (Tables 6-10). All other combinations (multiple models not reported directly due to space limit) robustly confirm the results reported and presented in the paper.

4.3.1 Study limitations

Modeling and estimating ΔCoVaR is associated with certain limitations. Each model, including the one chosen for the current study, should be a universal model applicable to data from a wide range of European stock exchanges. The data itself, especially in the context of proxy usage, requires synchronization to address the issue of different days with and without quotations on individual stock exchanges. These issues can add uncertainty to the estimation of ΔCoVaR compared to an ideal situation when we have a set of homogeneous exchanges. We effectively address these challenges by using flexible GJR-GARCH and GARCH-DCC models with small lag orders in the autoregressions, which permits avoiding over-parameterizing the models while maintaining the coherence of their design in every system. Concerning different listing days, we consistently assume that if on a given day there are fewer banks traded (internally or externally), then on these days, the system consists of a smaller number of banks. Thus we proportionally recalculate the systemic importance weights on a daily, dynamic basis.

Dynamic panel models also have certain limitations, including the need to meet the assumptions regarding the conditions of moment correctness and the limitations regarding the exogeneity of instruments. To allow for the introduction of the endogenous effects and non-linear relationships into the model, we constructed interactive variables, introduced autoregressive variables, and allowed for multiple iterations of the EX_SYS variable. At the same time, we applied dynamic estimation methods (SGMM) to accommodate these variables. Acquiring relevant panel data, especially in the face of the temporal gaps in research variable time series, particularly for emerging and frontier markets, presented an additional challenge. To minimize the impact of these limitations on the obtained results, we maximized the sample size by using and manually combining the data from five different databases. Additionally, the selection of appropriate control variables could be arbitrary. To tackle this problem, we conducted thorough preliminary literature studies – to maximize the size of the initial control variables set, and we conducted numerous preliminary statistical analyses to optimize the set by selecting suitable variables versus their correlation properties (see Table 4).

The data limitations regarding the time span of the ongoing crisis related to the war in Ukraine mean that the results regarding this crisis presented in this study need to be treated with caution. As the conflict progresses, so may change the nature of the underlying crisis, and new conclusions may follow. Furthermore, additional macroeconomic effects that typically occur with significant time lags may manifest in the future. Thus, it is reasonable to repeat the study once the crisis has subsided to verify if the conclusions hold for the whole war-related crisis or not just for its initial phase, which we investigated in this paper.

5 Conclusions

The paper presented a cross-sectional analysis of systemic risk and its impact on the TCR of systemically important European banks, combining the panel vector autoregression models (VAR) with ΔCoVaR-based systemic risk measurement, investigating the intertwined processes involving a large set of exogenous and endogenous variables. We captured various systematic relationships during the European public debt crisis, Brexit, the COVID-19 pandemic, and the war in Ukraine. The results offer macroprudential insights.

We empirically captured several effects from the economic theory. We also verified the intuitions behind the results reported in financial stability reports and the literature, concluding about the properties of systemic turbulence and its impact on total capital ratios of systemically important banks. Concerning both research hypotheses, we confirmed that systemic risk captured by ΔCoVaR has a significant positive effect on the TCR in the periods leading to crises and a strong negative effect in the crisis aftermath. We validate this relationship in all turbulent periods, including the war in Ukraine.

We also verified that systemic risk modifies the impact of such macroeconomic indicators as real GDP growth, public debt, and current accounts balance on the capital position of banks, which effectively may turn the direction of this impact around. Specifically, we found that any positive effects on the TCR of the GDP growth and current accounts balance dynamics weaken in the face of systemic risk – turning negative in high turbulence. Interestingly, the study confirmed that a negative effect of the increasing public debt on the TCR becomes positive in the presence of systemic turbulence. Such an effect might be related to the numerous liquidity and quantitative easing programs.

We included 27 housing markets and the US stock market among the studied market indicators. The study showed that, based on the data for 2010-2022, banks' ability to build robust capital does not strongly depend on the housing market dynamics, even when intertwined with a systemic crisis. The results show a potentially consistent but statistically weak effect (p-values between 9 and 13%). This suggests that commercial systemically important European banks manage the changing housing price trends relatively well. Such an effect is consistent for all the turbulent periods under investigation, including the crisis in 2022. Since the analyzed period does not include the global financial crisis, the study implies that the importance of this particular risk factor for commercial banks decreased after 2009, after the macroprudential reforms that came afterward.

In contrast, we confirmed the effect of the US stock market on the TCR in all studied dimensions, including the crisis in 2022. It was found to affect the capital ratios of the studied banks regardless of the level of systemic risk. However, this effect was strong and positive in calm periods and equally strong but negative when coupled with systemic turbulence. Importantly, we captured the effects of the American stock exchange, even though we studied European banks. Importantly, about half of the studied banks are not listed at all. Thus, our results strongly point to spillovers of systemic-risk-induced effects on the TCR between the US and Europe for both listed and unlisted banks.

The effects identified for the crisis in 2022 show a considerable resemblance to the results discussed above, indicating that the current crisis affects banks' TCRs similarly to previous crises that were much more financial in nature. One identified difference relates to the effects of the GDP growth dynamics. However, these effects could not be robustly confirmed at this point, possibly because the current crisis is still too young for them to manifest fully. The second difference relates to the effects generated by the US stock market that seem weaker during the current crisis compared to other crises.

Funding and conflicts of interest

The authors declare no conflicts of interest regarding the study. The National Science Centre funded this research project under Agreement UMO2018/29/N/HS4/02783.

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Figure 1 ΔCoVaR Estimations for Systemically Important Banks in Europe 2010-2023

This figure presents the results of the estimations of ΔCoVaR between 2010 and 2023. The results for the European-Union-wide banking sector are marked in black, and the 27 European countries are marked in color. Computations were executed in the R environment based on approx.295,000 data entries. Irregular peaks recorded for Malta in 2022-20223 capture the instability of the Bank of Valetta, as well as the legal irregularities and reputation risk related to the Deiulemar case.

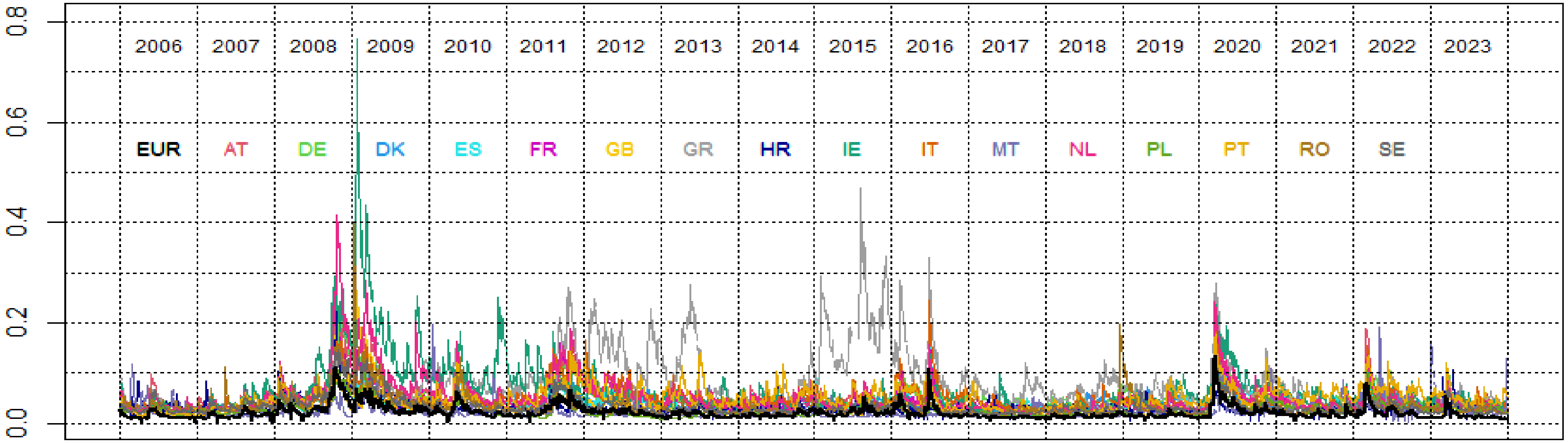

Figure 2 ΔCoVaR estimations for Systemically Important Banks in Europe 2010-2023 – quantile distributions

This figure presents the distribution quantiles for the ΔCoVaR estimations for 27 European countries sampled between 2010 and 2023 presented in Figure 1. Computations were executed in the R environment based on approx.295,000 data entries.

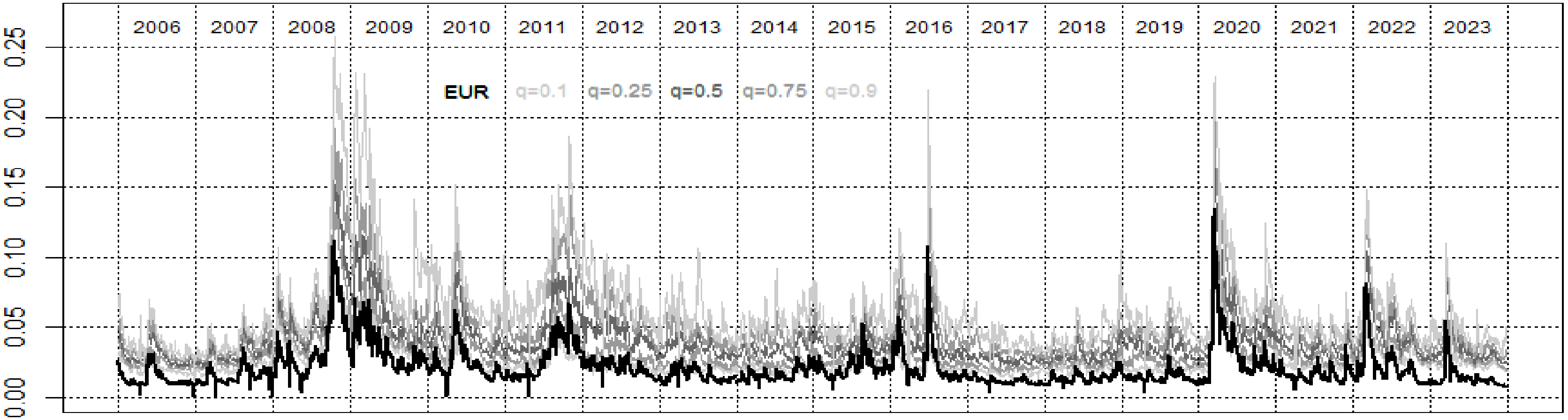

Table 1. Characteristics of experimental variables used in the panel study

This table describes the experimental variables used in the panel studies and their sources and calculation methods.

Variable	Description	Source
	EX.VAR – basic experimental variables	
GDP_CAP	Real GDP per capita growth	World Bank (2023)
DEBT_GDP	General government gross debt to GDP ratio	International Monetary Fund (2023)
CAB_GDP	Current accounts balance to GDP ratio (annual pp. change)	International Monetary Fund (2023)
HOUSE	Change in real house price (annual pp. change)	Calculated using the European Mortgage Federation (2021, 2023) data
STOCKM	0.05-quantile of the daily returns of the S&P500 index within each year	Calculated using the Eikon (2023) data
EX_SYS	Systemic risk variable based on the ΔCoVaR of the European-Union-wide banking sector model (baseline model)	Estimated using Eikon (2023) data
EX_SYS_1	Systemic risk variable based on ΔCoVaR of the European-Union-wide banking sector lagged by one year (lagged baseline model)	Estimated using Eikon (2023) data
EX_SYS_R	Systemic risk variable based on the ΔCoVaR of a portfolio of banking sectors of selected European countries (robustness model)	Estimated using Eikon (2023) data
EX_SYS_1_R	Systemic risk variable based on ΔCoVaR of a portfolio of banking sectors of selected European countries lagged by one year (lagged robustness model)	Estimated using Eikon (2023) data
	EX.VAR – interactive experimental variables	
EX_GDP_CAP	The product of the EX_SYS variable and the GDP_CAP variable	Calculated using the World Bank (2023) data
EX_GDP_CAP_R	The product of the EX_SYS_R variable and the GDP_CAP variable (robustness model)	Calculated using the World Bank (2023) data
EX_DEBT_GDP	The product of the EX_SYS variable and the DEBT_GDP variable	Calculated using the International Monetary Fund (2023) data
EX_DEBT_GDP_R	The product of the EX_SYS_R variable and the DEBT_GDP variable (robustness model)	Calculated using the International Monetary Fund (2023) data
EX_CAB_GDP	The product of the EX_SYS variable and the CAB_GDP variable	Calculated using the International Monetary Fund (2023) data
EX_CAB_GDP_R	The product of the EX_SYS_R variable and the CAB_GDP variable (robustness model)	Calculated using the International Monetary Fund (2023) data
EX_HOUSE	The product of the EX_SYS variable and the HOUSE variable	Calculated using the European Mortgage Federation (2021, 2023) data
EX_HOUSE_R	The product of the EX_SYS_R variable and the HOUSE variable (robustness model)	Calculated using the European Mortgage Federation (2021, 2023) data
EX_STOCKM	The product of the EX_SYS variable and the STOCKM variable	Calculated using the Eikon (2023) data
EX_STOCKM_R	The product of the EX_SYS_R variable and the STOCKM variable (robustness model)	Calculated using the Eikon (2023) data
EX_GDP_CAP_2022	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_GDP_CAP variable	Calculated using the World Bank (2023) data
EX_GDP_CAP_2022_R	The product of the binary variable WAR (1 - for 2022, 0 – for 2010-2021 period) and the EX_GDP_CAP_R variable (robustness model)	Calculated using the World Bank (2023) data
EX_DEBT_GDP_2022	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_DEBT_GDP variable	Calculated using the International Monetary Fund (2023) data
EX_DEBT_GDP_2022_R	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_DEBT_GDP_R variable (robustness model)	Calculated using the International Monetary Fund (2023) data
EX_CAB_GDP_2022	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_CAB_GDP variable	Calculated using the International Monetary Fund (2023) data
EX_CAB_GDP_2022_R	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_CAB_GDP_R variable (robustness model)	Calculated using the International Monetary Fund (2023) data
EX_HOUSE_2022	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_HOUSE variable	Calculated using the European Mortgage Federation (2021, 2023) data
EX_HOUSE_2022_R	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_HOUSE_R variable (robustness model)	Calculated using the European Mortgage Federation (2021, 2023) data
EX_STOCKM_2022	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_STOCKM variable	Calculated using the Eikon (2023) data
EX_STOCKM_2022_R	The product of the binary variable WAR (1 - for 2022, 0 – for the 2010-2021 period) and the EX_STOCKM_R variable (robustness model)	Calculated using the Eikon (2023) data

Table 2. Description of control variables used in the panel study

This table describes the dependent and control variables used in the panel studies. The data originates from the BankFocus (2023) database.

Variable	Description	Previous research
TCR	Total capital adequacy ratio	(Anginer et al., 2021; Ernaningsih et al., 2023; Feghali et al., 2021; Harkati et al., 2020; Ozili, 2018; Stewart et al., 2021; Yudaruddin et al., 2023)
		MACROECON.VAR – macroeconomic variables
CPI	Inflation, consumer prices	(Adusei, 2015; Elnahass et al., 2022; Ernaningsih et al., 2023; Ghenimi et al., 2017; Samarasinghe, 2023; Vu et al., 2023)
UN	Unemployment, total (% of the total labor force)	(Asteriou et al., 2021; Danisman & Tarazi, 2020; Koetter & Poghosyan, 2010; Ozili, 2018; Shim, 2019)
		BANK.VAR - unit-specific variables characterizing the specific operation of a given bank
CtI	Cost-to-income ratio	(Dietrich & Wanzenried, 2011; Ghenimi et al., 2017; Tran et al., 2022; Vu et al., 2023; Yudaruddin et al., 2023)

DEPO_D	Total customer deposits growth	(Martins et al., 2019; Samarasinghe, 2023; Yakubu & Abokor, 2020)
LA_TA	Liquid assets to total assets ratio	(Adusei, 2015; Le, 2021; Shim, 2019; Trad et al., 2017; Tran et al., 2022)
LN_TA	Natural logarithm of total assets	(Abdul Karim et al., 2014; Adusei, 2015; Ernaningsih et al., 2023; Ghenimi et al., 2017; Harkati et al., 2020)
LOAN_D	Gross loans & advances to customers' growth	(Al-Khouri & Arouri, 2016; Ernaningsih et al., 2023; Ghenimi et al., 2017; Le, 2020)
LOAN_DEPO	Gross loans & advances to customers to customer deposits ratio	(Amanda, 2023; Bourkhis & Nabi, 2013; Han & Melecky, 2013; Kanga et al., 2021; Stewart et al., 2021)
NII_OR	Non-interest income to operating revenues ratio	(Ernaningsih et al., 2023; Le, 2020; Shim, 2019; Stiroh & Rumble, 2006; Tran et al., 2022)
NIM	Net interest margin	(Dietrich & Wanzenried, 2011; Ghenimi et al., 2017; Tran et al., 2022; Wang & Lin, 2021)

Table 3. Correlation matrix of the variables used in the panel study

This table presents the Pearson correlation coefficients for the dependent and independent variables in this study. The sample consists of 124 banks; the sample period for accounting data spans 2010 through 2022; the sample period for stock-market data spans from 2010 to 2023. All variables are defined in Tables 1 and 2.

	TCR	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	CPI	UN	GDP_CAP	DEBT_GDP
TCR	1,000												
NIM	-0,052	1,000											
NII_OR	0,122	-0,357	1,000										
CtI	-0,077	-0,165	-0,089	1,000									
LA_TA	0,303	-0,247	0,350	0,026	1,000								
LOAN_DEPO	-0,178	-0,126	-0,169	-0,038	-0,364	1,000							
LOAN_D	-0,039	-0,006	-0,007	-0,086	0,023	-0,025	1,000						
DEPO_D	0,067	-0,075	0,142	-0,021	0,103	-0,151	0,295	1,000					
LN_TA	-0,135	-0,458	0,213	0,100	0,081	0,189	-0,132	-0,064	1,000				
CPI	0,061	0,089	-0,029	-0,085	-0,004	-0,130	0,085	0,044	-0,057	1,000			
UN	-0,278	0,123	-0,130	0,015	-0,270	0,262	-0,069	-0,035	0,032	-0,270	1,000		
GDP_CAP	0,068	0,048	0,011	0,026	0,029	-0,053	-0,009	0,017	-0,163	-0,494	0,012	1,000	
DEBT_GDP	-0,321	-0,206	0,067	0,180	-0,158	0,046	-0,190	-0,073	0,441	-0,164	0,476	-0,086	1,000
CAB_GDP	-0,086	0,032	-0,027	0,060	-0,019	0,070	-0,065	-0,036	0,012	-0,198	0,133	0,140	0,002
HOUSE	-0,060	0,056	0,015	0,023	0,001	0,061	0,040	0,048	-0,090	-0,407	0,199	0,284	-0,022
STOCKM	-0,050	0,027	0,015	0,012	0,004	0,064	-0,008	-0,050	-0,037	-0,340	0,138	0,520	-0,014
EX_SYS	0,121	-0,039	0,018	-0,017	0,030	-0,082	-0,008	0,039	0,017	0,046	-0,108	-0,289	0,036
EX_GDP_CAP	-0,020	0,072	0,000	0,009	0,006	0,047	-0,012	-0,011	-0,118	-0,408	0,115	0,873	-0,100
EX_DEBT_GDP	-0,080	-0,131	0,060	0,073	-0,056	-0,047	-0,089	-0,004	0,234	-0,066	0,142	-0,283	0,554
EX_CAB_GDP	-0,055	0,023	-0,013	0,057	-0,008	0,053	-0,041	-0,027	0,021	-0,207	0,051	0,215	-0,063
EX_HOUSE	0,000	0,041	0,014	-0,001	0,025	0,044	0,034	0,047	-0,078	-0,405	0,144	0,251	-0,060
EX_STOCKM	-0,125	0,057	-0,009	0,005	-0,029	0,098	0,011	-0,052	-0,034	-0,142	0,144	0,469	-0,041
EX_GDP_CAP_R_2022	-0,085	-0,001	0,053	0,076	0,005	0,079	-0,065	-0,035	0,016	-0,808	0,164	0,453	0,068
EX_DEBT_GDP_2022	0,071	-0,028	0,038	-0,026	-0,004	-0,113	0,020	0,093	0,088	0,628	-0,123	-0,271	0,130
EX_CAB_GDP_2022	-0,087	-0,009	-0,005	0,023	-0,008	0,129	-0,042	-0,046	-0,004	-0,597	0,142	0,289	-0,036
EX_HOUSE_2022	-0,069	0,043	0,036	0,059	0,039	0,027	-0,025	-0,036	-0,044	-0,631	0,157	0,354	0,058
EX_STOCKM_2022	-0,109	0,001	-0,004	0,045	-0,005	0,107	-0,036	-0,075	-0,038	-0,807	0,187	0,369	0,003
EX_SYS_R	0,103	-0,043	0,019	-0,020	0,026	-0,081	-0,019	0,044	0,025	0,118	-0,099	-0,421	0,038
EX_GDP_CAP_R	-0,015	0,062	0,005	0,009	0,012	0,044	-0,007	-0,011	-0,111	-0,400	0,093	0,877	-0,106
EX_DEBT_GDP_R	-0,093	-0,139	0,064	0,074	-0,059	-0,048	-0,097	0,004	0,248	-0,022	0,155	-0,375	0,573
EX_CAB_GDP_R	-0,071	0,019	-0,021	0,052	-0,022	0,064	-0,045	-0,027	0,023	-0,212	0,074	0,204	-0,051
EX_HOUSE_R	0,006	0,026	0,020	0,002	0,032	0,041	0,039	0,047	-0,071	-0,408	0,132	0,254	-0,064
EX_STOCKM_R	-0,126	0,063	-0,012	0,005	-0,029	0,103	0,015	-0,055	-0,038	-0,168	0,147	0,516	-0,043
EX_GDP_CAP_R_2022_R	-0,085	-0,001	0,053	0,076	0,005	0,079	-0,065	-0,035	0,016	-0,808	0,164	0,453	0,068
EX_DEBT_GDP_2022_R	0,071	-0,028	0,038	-0,026	-0,004	-0,113	0,020	0,093	0,088	0,628	-0,123	-0,271	0,130
EX_CAB_GDP _2022_R	-0,087	-0,009	-0,005	0,023	-0,008	0,129	-0,042	-0,046	-0,004	-0,597	0,142	0,289	-0,036
EX_HOUSE _2022_R	-0,069	0,043	0,036	0,059	0,039	0,027	-0,025	-0,036	-0,044	-0,631	0,157	0,354	0,058
EX_STOCKM_2022_R	-0,109	0,001	-0,004	0,045	-0,005	0,107	-0,036	-0,075	-0,038	-0,807	0,187	0,369	0,003

	CAB_GDP	HOUSE	STOCKM	EX_SYS	EX_GDP_CAP	EX_DEBT_GDP	EX_CAB_GDP	EX_HOUSE	EX_STOCKM	EX_GDP_CAP_2022	EX_DEBT_GDP_2022	EX_CAB_GDP_2022	EX_HOUSE_2022
CAB_GDP	1,000												
HOUSE	0,093	1,000											
STOCKM	0,114	0,152	1,000										
EX_SYS	-0,075	-0,030	-0,647	1,000									
EX_GDP_CAP	0,055	-0,005	0,365	-0,249									
EX_GDP_CAP_R	0,177	0,237	0,635	-0,381	1,000								
EX_DEBT_GDP	-0,093	-0,063	-0,489	0,750	-0,397	1,000							
EX_CAB_GDP	0,800	0,082	0,080	-0,053	0,273	-0,134	1,000						
EX_HOUSE	0,071	0,862	0,103	0,056	0,232	-0,023	0,083	1,000					
EX_STOCKM	0,074	0,082	0,851	-0,892	0,636	-0,684	0,050	0,003	1,000				
EX_GDP_CAP_R_2022	0,199	0,378	0,301	-0,164	0,410	-0,058	0,226	0,406	0,199	1,000			
EX_DEBT_GDP_2022	-0,223	-0,278	-0,331	0,180	-0,230	0,224	-0,254	-0,292	-0,219	-0,578	1,000		
EX_CAB_GDP_2022	0,306	0,256	0,276	-0,150	0,254	-0,130	0,355	0,270	0,182	0,628	-0,705	1,000	
EX_HOUSE_2022	0,159	0,467	0,271	-0,147	0,317	-0,055	0,180	0,507	0,179	0,776	-0,526	0,496	1,000
EX_STOCKM_2022	0,232	0,366	0,378	-0,206	0,321	-0,138	0,263	0,388	0,250	0,796	-0,874	0,728	0,716
EX_SYS_R	-0,062	-0,053	-0,642	0,927	-0,487	0,703	-0,055	0,040	-0,889	-0,189	0,207	-0,173	-0,170
EX_GDP_CAP_R	0,170	0,249	0,624	-0,393	0,987	-0,405	0,277	0,236	0,640	0,414	-0,227	0,253	0,318
EX_DEBT_GDP_R	-0,078	-0,085	-0,479	0,686	-0,467	0,955	-0,138	-0,041	-0,672	-0,069	0,246	-0,145	-0,065
EX_CAB_GDP_R	0,810	0,073	0,094	-0,064	0,277	-0,141	0,986	0,079	0,061	0,234	-0,262	0,365	0,186
EX_HOUSE_R	0,064	0,863	0,095	0,053	0,228	-0,027	0,079	0,993	-0,001	0,410	-0,294	0,272	0,512
EX_STOCKM_R	0,071	0,087	0,827	-0,844	0,676	-0,653	0,053	0,007	0,983	0,212	-0,232	0,193	0,190
EX_GDP_CAP_R_2022_R	0,199	0,378	0,301	-0,164	0,410	-0,058	0,226	0,406	0,199	1,000	-0,578	0,628	0,776
EX_DEBT_GDP_2022_R	-0,223	-0,278	-0,331	0,180	-0,230	0,224	-0,254	-0,292	-0,219	-0,578	1,000	-0,705	-0,526
EX_CAB_GDP_2022_R	0,306	0,256	0,276	-0,150	0,254	-0,130	0,355	0,270	0,182	0,628	-0,705	1,000	0,496
EX_HOUSE_2022_R	0,159	0,467	0,271	-0,147	0,317	-0,055	0,180	0,507	0,179	0,776	-0,526	0,496	1,000
EX_STOCKM_2022_R	0,232	0,366	0,378	-0,206	0,321	-0,138	0,263	0,388	0,250	0,796	-0,874	0,728	0,716

	EX_STOCKM_2022	EX_SYS_R	EX_GDP_CAP_R	EX_DEBT_GDP_R	EX_CAB_GDP_R	EX_HOUSE_R	EX_STOCKM_R	EX_GDP_CAP_R_2022_R	EX_DEBT_GDP_2022_R	EX_CAB_GDP_2022_R	EX_HOUSE_2022_R	EX_STOCKM_2022_R
EX_STOCKM_2022	1,000											
EX_SYS_R	-0,237	1,000										
EX_GDP_CAP_R	0,319	-0,524	1,000									
EX_DEBT_GDP_R	-0,155	0,739	-0,498	1,000								
EX_CAB_GDP_R	0,272	-0,050	0,273	-0,128	1,000							
EX_HOUSE_R	0,391	0,034	0,237	-0,050	0,068	1,000						
EX_STOCKM_R	0,266	-0,908	0,691	-0,687	0,057	0,006	1,000					
EX_GDP_CAP_R_2022_R	0,796	-0,189	0,414	-0,069	0,234	0,410	0,212	1,000				
EX_DEBT_GDP_2022_R	-0,874	0,207	-0,227	0,246	-0,262	-0,294	-0,232	-0,578	1,000			
EX_CAB_GDP_2022_R	0,728	-0,173	0,253	-0,145	0,365	0,272	0,193	0,628	-0,705	1,000		
EX_HOUSE_2022_R	0,716	-0,170	0,318	-0,065	0,186	0,512	0,190	0,776	-0,526	0,496	1,000	
EX_STOCKM_2022_R	1,000	-0,237	0,319	-0,155	0,272	0,391	0,266	0,796	-0,874	0,728	0,716	1,000

Table 4. Descriptive statistics of the variables used in the panel study

This table presents the summary statistics of variables. The sample consists of 130 banks, and the sample period spans 2010 through 2022. The table reports the mean, standard deviation, min, and max. All variables are defined in Tables 1 and 2.

	TCR	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	CPI	UN	GDP_CAP	DEBT_GDP
Mean	0,189	0,026	0,356	0,584	0,290	1,038	0,041	0,058	17,796	0,023	0,066	-0,005	0,573
Std. dev.	0,045	0,011	0,100	0,152	0,092	0,454	0,147	0,109	1,845	0,030	0,030	0,034	0,307
Min	0,009	0,010	0,130	0,196	0,063	0,385	-0,486	-0,493	14,080	-0,021	0,020	-0,112	0,152
Max	0,450	0,067	0,766	1,165	0,610	3,695	1,991	0,557	21,753	0,153	0,161	0,076	1,149

	CAB_GDP	HOUSE	STOCKM	EX_SYS	EX_GDP_CAP	EX_DEBT_GDP	EX_CAB_GDP	EX_HOUSE	EX_STOCKM	EX_GDP_CAP_2022	EX_DEBT_GDP_2022	EX_CAB_GDP_2022	EX_HOUSE_2022
Mean	0,001	0,005	-0,017	2,605	-0,032	1,515	0,001	0,010	-0,053	-0,018	0,170	-0,003	-0,029
Std. dev.	0,021	0,053	0,007	1,935	0,156	1,562	0,077	0,191	0,060	0,069	0,674	0,030	0,147
Min	-0,048	-0,283	-0,034	1,000	-0,603	0,166	-0,315	-1,131	-0,235	-0,446	0,000	-0,160	-1,131
Max	0,084	0,155	-0,005	7,000	0,457	8,043	0,252	0,388	-0,005	0,000	4,172	0,176	0,000

	EX_STOCKM_2022	EX_SYS_R	EX_GDP_CAP_R	EX_DEBT_GDP_R	EX_CAB_GDP_R	EX_HOUSE_R	EX_STOCKM_R	EX_GDP_CAP_2022_R	EX_DEBT_GDP_2022_R	EX_CAB_GDP_2022_R	EX_HOUSE_2022_R	EX_STOCKM_2022_R
Mean	-0,008	2,529	-0,040	1,469	-0,001	0,009	-0,051	-0,018	0,170	-0,003	-0,029	-0,008
Std. dev.	0,028	1,773	0,151	1,459	0,071	0,186	0,059	0,069	0,674	0,030	0,147	0,028
Min	-0,105	1,000	-0,603	0,170	-0,315	-1,131	-0,235	-0,446	0,000	-0,160	-1,131	-0,105
Max	0,000	7,000	0,381	8,043	0,198	0,364	-0,005	0,000	4,172	0,176	0,000	0,000

Table 5. Determinants of bank total capital ratio - panel data regression (GMM-SYS dynamic model; Models 1-7)

This table presents the results for the one-step system generalized method of moments (SYS-GMM). The sample period spans from 2010 through 2022. Model 1 shows the impact of five wider-market indicators on the TCR without considering systemic risk. Models 2, 4, 6, and 8 show the impact of the same indicators on TCR, considering unlagged systemic risk. Models 3 and 7, reduced to statistically significant independent variables, show the impact of these indicators on TCR, considering unlagged systemic risk. Models 5 and 7, reduced to statistically significant independent variables, show the impact of the indicators on TCR, considering lagged systemic risk. Models 5-7 replicate the analysis from Models 2-4 using alternative estimations of ΔCoVaR provided for robustness analysis. All the variables are defined in Tables 1 and 2. Number of banks: 118; number of observations: Models 1, 2, and 5: 1226; Models 3, 4, 6, and 7: 1227. AR (1) – 1st order autocorrelation test. AR (2) – 2nd order autocorrelation test. Robust standard errors in parentheses and p-values in brackets. *** significance at the level of 1%, ** significance at the level of 5%, *significance at the level of 10%, # significance at the level of 10,5%.

Model number	TCR (-1)	GDP_CAP	DEBT_GDP	CAB_GDP	HOUSE	STOCKM	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	CPI	UN	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
1	0,805*** (0,048)	-0,047 (0,037)	-0,013** (0,005)	0,03 (0,023)	0,019 (0,014)	-0,119 (0,137)					-0,102*** (0,027)	0,015 (0,03)	-0,135 (0,13)	0,001 (0,01)	-0,006 (0,009)	0,015 (0,013)	-0,002 (0,003)	-0,037*** (0,011)	0,009*** (0,003)	-0,001 (0)	0,066*** (0,017)	0 0,089	0,071
2	0,783*** (0,051)	-0,038 (0,038)	-0,014*** (0,005)	0,025 (0,024)	0,019 (0,014)	0,068 (0,161)	0,001# (0,001)				-0,08** (0,032)	0,018 (0,031)	-0,144 (0,134)	0,002 (0,01)	-0,005 (0,009)	0,017 (0,013)	-0,002 (0,003)	-0,036*** (0,011)	0,009*** (0,003)	-0,001 (0,001)	0,069*** (0,018)	0 0,115	0,072
3	0,772*** (0,045)						0,001** (0)				-0,071*** (0,021)	-0,037*** (0,014)				0,024* (0,014)		-0,037*** (0,011)	0,009*** (0,003)	-0,002*** (0)	0,069*** (0,012)	0 0,115	0,059
4	0,791*** (0,043)							-0,001** (0)			-0,067*** (0,021)	-0,039*** (0,014)				0,024* (0,013)		-0,037*** (0,011)	0,009*** (0,003)	-0,001*** (0)	0,069*** (0,013)	0 0,059	0,052
5	0,782*** (0,051)	-0,021 (0,041)	-0,014*** (0,005)	0,021 (0,023)	0,019 (0,014)	0,089 (0,151)			0,002** (0,001)		-0,074** (0,031)	0,019 (0,031)	-0,135 (0,133)	0,001 (0,01)	-0,005 (0,009)	0,018 (0,013)	-0,002 (0,003)	-0,036*** (0,011)	0,009*** (0,003)	-0,001 (0,001)	0,066*** (0,018)	0 0,15	0,08
6	0,775*** (0,044)								0,001*** (0)		-0,078*** (0,021)	-0,037** (0,015)				0,024* (0,014)		-0,036*** (0,011)	0,009*** (0,003)	-0,002*** (0)	0,068*** (0,012)	0 0,169	0,074
7	0,786*** (0,043)									-0,001* (0)	-0,067*** (0,021)	-0,039*** (0,014)				0,024* (0,013)		-0,037*** (0,011)	0,009*** (0,003)	-0,001*** (0)	0,07*** (0,013)	0 0,066	0,054

Table 6. Estimation results related to public debt – panel data regression (GMM-SYS dynamic model; Models 8-11 and 28-31)

This table presents the results of the one-step system generalized method of moments (SYS-GMM). The sample period spans 2010 through 2022. Model 8 delineates the effects of lagged systemic risk, Debt to GDP ratio, and the interaction between systemic risk and Debt to GDP ratio on TCR. Model 9 delineates the effects of unlagged systemic risk, Debt to GDP ratio, and the interaction between the binary WAR variable and the interaction between systemic risk and Debt to GDP on TCR. Models 10 and 11 replicate the analysis from Models 8 and 9 using alternative estimations of ΔCoVaR provided for robustness analysis. Models 28-31 present further robustness checks, replicating the analysis from Models 8-11 using all studied independent variables in a simultaneous panel study. All variables are defined in Tables 1 and 2. Number of banks: 118; number of observations: 1227. AR (1) – 1st order autocorrelation test. AR (2) – 2nd order autocorrelation test. Robust standard errors in parentheses and p-values in brackets. *** significance at the level of 1%, ** significance at the level of 5%, *significance at the level of 10%.

Results

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	DEBT_GDP	DEBT_GDP_R	EX_DEBT_GDP	EX_DEBT_GDP_R	EX_DEBT_GDP_2022	EX_DEBT_GDP_2022_R	CPI	UN	LA_TA	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
8	0,797***		-0,001*			-0,015***		0,001**				-0,066***	0,013	0,021*	-0,038***	0,009***	0	0,055***	0	
	(0,042)		(0)			(0,005)		(0)				(0,021)	(0,025)	(0,013)	(0,011)	(0,003)	(0)	(0,01)	0,123	0,067
9	0,774***	0,001**					-0,016***			0,004***		-0,139***	0,02	0,022*	-0,037***	0,008***	0	0,057***	0	
	(0,043)	(0)					(0,005)			(0,001)		(0,035)	(0,026)	(0,013)	(0,011)	(0,003)	(0)	(0,011)	0,131	0,036
10	0,79***				0	-0,017***			0,001***			-0,072***	0,017	0,021*	-0,038***	0,009***	0	0,055***	0	
	(0,041)				(0)	(0,005)			(0)			(0,021)	(0,026)	(0,013)	(0,011)	(0,003)	(0)	(0,011)	0,219	0,069
11	0,776***			0,001***			-0,016***				0,004***	-0,146***	0,02	0,022*	-0,037***	0,008***	0	0,056***	0	
	(0,042)			(0)			(0,005)				(0,001)	(0,035)	(0,026)	(0,013)	(0,011)	(0,003)	(0)	(0,011)	0,205	0,046

Panel robustness tests

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	DEBT_GDP	DEBT_GDP_R	EX_DEBT_GDP	EX_DEBT_GDP_R	EX_DEBT_GDP_2022	EX_DEBT_GDP_2022_R	CPI	UN	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
28	0,793***		-0,001**			-0,015***		0,001**				-0,073***	0,022	-0,153	0,001	-0,006	0,017	-0,002	-0,038***	0,008***	-0,001	0,069***	0	0,069
	(0,044)		(0)			(0,005)		(0)				(0,022)	(0,031)	(0,13)	(0,01)	(0,009)	(0,013)	(0,003)	(0,011)	(0,003)	(0)	(0,018)	0,1	
29	0,771***	0,001**					-0,017***			0,003***		-0,141***	0,029	-0,151	0,001	-0,005	0,018	-0,002	-0,037***	0,008***	-0,001	0,071***	0	0,037
	(0,045)	(0)					(0,006)			(0,001)		(0,035)	(0,032)	(0,133)	(0,01)	(0,009)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,111	
30	0,786***				0	-0,017***			0,001***			-0,078***	0,026	-0,146	0,001	-0,005	0,017	-0,002	-0,037***	0,008***	-0,001	0,068***	0	0,073
	(0,043)				(0)	(0,006)			(0)			(0,022)	(0,032)	(0,13)	(0,01)	(0,009)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,183	
31	0,773***			0,001***			-0,017***				0,003***	-0,148***	0,029	-0,14	0,001	-0,005	0,018	-0,002	-0,036***	0,008***	-0,001	0,069***	0	0,051
	(0,045)			(0)			(0,006)				(0,001)	(0,035)	(0,032)	(0,132)	(0,01)	(0,009)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,178	

Table 7. Estimation results related to GDP - panel data regression (GMM-SYS dynamic model; Models 12-15 and 32-35)

This table presents the results for the one-step system generalized method of moments (SYS-GMM). The sample period spans 2010 through 2022. Model 12 delineates the effects of the lagged systemic risk, the real GDP per capita growth, and the interaction between systemic risk and real GDP per capita growth on TCR. Model 13 delineates the effects of unlagged systemic risk, the real GDP per capita growth, and the interaction between the binary WAR variable and the interaction between systemic risk and the real GDP per capita growth on the TCR. Models 14 and 15 replicate the analysis from Models 12 and 13 using alternative estimations of ΔCoVaR provided for robustness analysis. Models 32-35 present further robustness checks, replicating the analysis in Models 12-15 using all studied independent variables in a simultaneous panel study. All the variables are defined in Tables 1 and 2. Number of banks: 118; number of observations: 1227. AR (1) – 1st order autocorrelation test. AR (2) – 2nd order autocorrelation test. Robust standard errors in parentheses and p-values in brackets. *** significance at the level of 1%, ** significance at the level of 5%, *significance at the level of 10%, #significance at the level of 12%.

Results

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	GDP_CAP	GDP_CAP_R	EX_GDP_CAP	EX_GDP_CAP_R	EX_GDP_CAP 2022	EX_GDP_CAP 2022_R	CPI	UN	LA_TA	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
14	0,781***		0			0,079			-0,026***			-0,069**	-0,031**	0,024*	-0,037***	0,009***	-0,001***	0,07***	0	0,107
	(0,044)		(0)			(0,059)			(0,01)			(0,031)	(0,015)	(0,014)	(0,011)	(0,003)	(0)	(0,012)	0,065	
15	0,774***	0,001#					-0,025				-0,023	-0,136**	-0,044***	0,024*	-0,037***	0,009***	-0,002***	0,074***	0	0,063
	(0,048)	(0,001)					(0,036)				(0,019)	(0,059)	(0,014)	(0,014)	(0,011)	(0,003)	(0)	(0,012)	0,116	
16	0,775***				0,001	0,115		-0,037***				-0,066*	-0,03*	0,025*	-0,037***	0,009***	-0,001***	0,069***	0	0,085
	(0,044)				(0,001)	(0,07)		(0,012)				(0,035)	(0,016)	(0,014)	(0,011)	(0,003)	(0)	(0,012)	0,076	
17	0,77***			-0,001*			-0,006			-0,024		-0,13**	-0,042***	0,025*	-0,036***	0,009***	-0,002***	0,072***	0	0,092
	(0,048)			(0)			(0,04)			(0,019)		(0,057)	(0,014)	(0,014)	(0,011)	(0,003)	(0)	(0,012)	0,156	

Panel robustness tests

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	GDP_CAP	GDP_CAP_R	EX_GDP_CAP	EX_GDP_CAP_R	EX_GDP_CAP_2022	EX_GDP_CAP_2022_R	CPI	UN	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
34	0,779***		0			0,119*		-0,038***				-0,071**	-0,028*	-0,075	-0,001	-0,007	0,026*	0,002	-0,037***	0,009***	-0,002***	0,075***	0	0,097
	(0,045)		(0)			(0,071)		(0,012)				(0,033)	(0,017)	(0,135)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,019)	0,059	
35	0,775***	0,001*					-0,011			-0,034*		-0,161***	-0,042***	-0,071	0	-0,006	0,025*	0,001	-0,036***	0,009***	-0,002***	0,078***	0	0,097
	(0,049)	(0,001)					(0,038)			(0,018)		(0,048)	(0,015)	(0,131)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,134	
36	0,785***				-0,001	0,082			-0,027***			-0,075***	-0,028*	-0,082	0	-0,007	0,025*	0,001	-0,037***	0,009***	-0,002***	0,077***	0	0,105
	(0,045)				(0)	(0,061)			(0,01)			(0,029)	(0,016)	(0,135)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,019)	0,051	
37	0,778***			0,001			-0,029				-0,035*	-0,168***	-0,042***	-0,078	0	-0,006	0,024*	0,001	-0,036***	0,009***	-0,002***	0,081***	0	0,083
	(0,049)			(0,001)			(0,034)				(0,018)	(0,05)	(0,014)	(0,131)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,095	

Table 8. Estimation results related to current accounts balance - panel data regression (GMM-SYS dynamic model; Models 18-21 and 38-41)

This table presents the results of the one-step system generalized method of moments (SYS-GMM). The sample period spans 2010 through 2022. Model 18 delineates the effects of the lagged systemic risk, the annual percentage change of the CAB to GDP ratio, and the interaction between systemic risk and the CAB to GDP ratio on TCR. Model 19 delineates the effects of the unlagged systemic risk, CAB to GDP ratio, and the interaction between the binary WAR and the interaction between systemic risk and CAB to GDP ratio on TCR. Models 20 and 21 replicate the analysis from Models 18 and 19 using alternative estimations of ΔCoVaR provided for robustness analysis. Models 38-41 present further robustness checks, replicating the analysis from Models 18-21 using all studied independent variables in a simultaneous panel study. All variables are defined in Tables 1 and 2. Number of banks: Models 18-21: 118; number of observations: Models 18-21: 1227; Models 38-41: 1226. AR (1) – 1st order autocorrelation test. AR (2) – 2nd order autocorrelation test. Robust standard errors in parentheses and p-values in brackets. *** significance at the level of 1%, ** significance at the level of 5%, *significance at the level of 10%, #significance at the level of 12%.

Results

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	CAB_GDP	CAB_GDP_R	EX_CAB_GDP	EX_CAB_GDP_R	EX_CAB_GDP_2022	EX_CAB_GDP_2022_R	CPI	UN	LA_TA	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
18	0,802***		-0,001**			0,133**		-0,041***				-0,074***	-0,046***	0,022*	-0,037***	0,009***	-0,001***	0,067***	0	0,051
	(0,042)		(0)			(0,055)		(0,015)				(0,022)	(0,014)	(0,013)	(0,011)	(0,003)	(0)	(0,013)	0,093	
19	0,774***	0,001**					0,04#			-0,088***		-0,125***	-0,042***	0,024*	-0,036***	0,009***	-0,002***	0,071***	0	0,061
	(0,044)	(0)					(0,025)			(0,025)		(0,031)	(0,014)	(0,014)	(0,011)	(0,003)	(0)	(0,013)	0,123	
20	0,792***				-0,001*	0,094**			-0,027**			-0,07***	-0,042***	0,023*	-0,037***	0,009***	-0,001***	0,069***	0	0,056
	(0,043)				(0)	(0,041)			(0,012)			(0,022)	(0,015)	(0,013)	(0,011)	(0,003)	(0)	(0,013)	0,077	
21	0,776***			0,001***			0,039#				-0,086***	-0,131***	-0,042***	0,023*	-0,036***	0,008***	-0,002***	0,071***	0	0,071
	(0,044)			(0)			(0,025)				(0,025)	(0,03)	(0,015)	(0,013)	(0,011)	(0,003)	(0)	(0,013)	0,181	

Panel robustness tests

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	CAB_GDP	CAB_GDP_R	EX_CAB_GDP	EX_CAB_GDP_R	EX_CAB_GDP_2022	EX_CAB_GDP_2022_R	CPI	UN	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
38	0,806***		-0,001***			0,142***		-0,04***				-0,078***	-0,041***	-0,1	-0,001	-0,007	0,021	0	-0,037***	0,009***	-0,001***	0,076***	0	0,05
	(0,044)		(0)			(0,051)		(0,015)				(0,023)	(0,015)	(0,128)	(0,01)	(0,008)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,019)	0,081	
39	0,78***	0,001**					0,05**			-0,083***		-0,126***	-0,039***	-0,095	-0,001	-0,007	0,024*	0,001	-0,036***	0,009***	-0,002***	0,079***	0	0,072
	(0,046)	(0)					(0,025)			(0,023)		(0,03)	(0,015)	(0,129)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,019)	0,116	
40	0,796***				-0,001*	0,104***			-0,026**			-0,074***	-0,038**	-0,108	-0,001	-0,007	0,022*	0	-0,037***	0,009***	-0,002***	0,078***	0	0,069
	(0,044)				(0)	(0,039)			(0,012)			(0,023)	(0,015)	(0,129)	(0,01)	(0,008)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,019)	0,068	
41	0,782***			0,001***			0,05*				-0,081***	-0,132***	-0,039***	-0,083	-0,001	-0,007	0,024*	0,001	-0,036***	0,009***	-0,002***	0,077***	0	0,081
	(0,045)			(0)			(0,025)				(0,023)	(0,03)	(0,015)	(0,128)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,019)	0,172	

Table 9. Estimation results related to housing prices - panel data regression (GMM-SYS dynamic model; Models 22-25 and 42-45)

This table presents the results of the one-step system generalized method of moments (SYS-GMM). The sample period spans 2010 through 2022. Model 22 delineates the effects of the lagged systemic risk, housing price indices dynamics, and the interaction between systemic risk and housing price indices dynamics on TCR. Model 23 delineates the effects of the unlagged systemic risk, housing price indices dynamics, and the interaction between the binary WAR variable and the interaction between systemic risk and housing price indices dynamics on TCR. Models 24 and 25 replicate the analysis from Models 22 and 23 using alternative estimations of ΔCoVaR provided for robustness analysis. Models 42-45 present further robustness checks, replicating the analysis from Models 22-25 using all studied independent variables in a simultaneous panel study. All variables are defined in Tables 1 and 2. Number of banks: 118; number of observations: Models 22-25: 1227, Models 42-45: 1226. AR (1) – 1st order autocorrelation test. AR (2) – 2nd order autocorrelation test. Robust standard errors in parentheses and p-values in brackets. *** significance at the level of 1%, ** significance at the level of 5%, *significance at the level of 10%, #significance level at the level of 13%.

Results

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	HOUSE	HOUSE_R	EX_HOUSE	EX_HOUSE__R	EX_HOUSE__2022	EX_HOUSE_2022_R	CPI	UN	LA_TA	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
22	0,791***		-0,001**			0,024#		-0,002				-0,054**	-0,041***	0,023*	-0,037***	0,009***	-0,001***	0,068***	0	0,077
	(0,044)		(0)			(0,027)		(0,007)				(0,023)	(0,014)	(0,013)	(0,011)	(0,003)	(0)	(0,012)	0,049	
23	0,77***	0,001**					0,023#			-0,013#		-0,08***	-0,04***	0,025*	-0,036***	0,009***	-0,002***	0,07***	0	0,053
	(0,044)	(0)					(0,015)			(0,009)		(0,029)	(0,014)	(0,014)	(0,011)	(0,003)	(0)	(0,012)	0,091	
24	0,787***				-0,001*	0,04#			-0,007			-0,056**	-0,042***	0,023*	-0,037***	0,009***	-0,001***	0,069***	0	0,072
	(0,043)				(0)	(0,026)			(0,007)			(0,023)	(0,014)	(0,013)	(0,011)	(0,003)	(0)	(0,012)	0,053	
25	0,772***			0,001***			0,024#				-0,013#	-0,087***	-0,039***	0,025*	-0,036***	0,009***	-0,002***	0,069***	0	0,067
	(0,044)			(0)			(0,015)				(0,008)	(0,029)	(0,014)	(0,014)	(0,011)	(0,003)	(0)	(0,012)	0,138	

Panel robustness tests

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	HOUSE	HOUSE_R	EX_HOUSE	EX_HOUSE_R	EX_HOUSE_2022	EX_HOUSE_2022_R	CPI	UN	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
42	0,793***		-0,001**			0,027#		-0,003#				-0,06**	-0,036**	-0,123	-0,001	-0,007	0,022*	0	-0,037***	0,009***	-0,002***	0,079***	0	0,083
	(0,045)		(0)			(0,027)		(0,007)				(0,024)	(0,015)	(0,126)	(0,01)	(0,008)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,041	
43	0,774***	0,001**					0,024#			-0,014#		-0,087***	-0,036**	-0,095	0	-0,006	0,025*	0,001	-0,036***	0,009***	-0,002***	0,077***	0	0,059
	(0,046)	(0)					(0,015)			(0,009)		(0,031)	(0,015)	(0,127)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,078	
44	0,79***				-0,001*	0,043#			-0,008#			-0,062**	-0,037**	-0,125	-0,002	-0,007	0,023*	0	-0,037***	0,009***	-0,002***	0,079***	0	0,084
	(0,044)				(0)	(0,026)			(0,007)			(0,024)	(0,015)	(0,127)	(0,01)	(0,008)	(0,013)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,045	
45	0,776***			0,001***			0,024*				-0,014#	-0,093***	-0,036**	-0,083	0	-0,006	0,025*	0,001	-0,035***	0,009***	-0,002***	0,075***	0	0,078
	(0,045)			(0)			(0,015)				(0,009)	(0,03)	(0,015)	(0,127)	(0,01)	(0,008)	(0,014)	(0,003)	(0,011)	(0,003)	(0,001)	(0,018)	0,122	

Table 10. Estimation results related to the US stock market - panel data regression (GMM-SYS dynamic model; Models 26-29 and 46-49)

This table presents the results of the one-step system generalized method of moments (SYS-GMM). The sample period spans 2010 through 2022. Model 26 delineates the effects of the lagged systemic risk, the US stock market (quantile of returns distribution), and the interaction between systemic risk and the US stock market on TCR. Model 27 delineates the effects of the unlagged systemic risk, the US stock market, and the interaction between the binary WAR variable and the interaction between systemic risk and the US stock market on TCR. Models 28 and 29 replicate the analysis from Models 26 and 27 using alternative estimations of ΔCoVaR provided for robustness analysis. Models 46-49 present further robustness checks, replicating the analysis from Models 26-29 using all studied independent variables in a simultaneous panel study. All variables are defined in Tables 1 and 2. Number of banks: 118; number of observations: Models 26-29: 1227, Models 46-49: 1226. AR (1) – 1st order autocorrelation test. AR (2) – 2nd order autocorrelation test. Robust standard errors in parentheses and p-values in brackets. *** significance at the level of 1%, ** significance at the level of 5%, *significance at the level of 10%.

Results

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	STOCKM	STOCKM_R	EX_STOCKM	EX_STOCKM_R	EX_STOCKM_2022	EX_STOCKM_2022_R	CPI	UN	LA_TA	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
26	0,769*** (0,044)		-0,001*** (0)			1,009*** (0,25)		-0,133*** (0,025)				-0,011 (0,029)	-0,036** (0,014)	0,025* (0,014)	-0,036*** (0,012)	0,008*** (0,003)	-0,001*** (0)	0,083*** (0,012)	0 0,103	0,208
27	0,76*** (0,046)	0,001 (0,001)					-0,014 (0,155)			-0,136** (0,058)		-0,179*** (0,057)	-0,047*** (0,014)	0,025* (0,014)	-0,035*** (0,011)	0,008*** (0,003)	-0,002*** (0,001)	0,078*** (0,014)	0 0,109	0,044
28	0,767*** (0,044)				-0,001 (0)	0,753*** (0,214)			-0,12*** (0,023)			-0,039 (0,027)	-0,034** (0,015)	0,024* (0,014)	-0,036*** (0,012)	0,008*** (0,003)	-0,002*** (0)	0,08*** (0,013)	0 0,157	0,203
29	0,76*** (0,046)			0,001** (0,001)			0,089 (0,156)				-0,131** (0,056)	-0,174*** (0,054)	-0,047*** (0,015)	0,025* (0,014)	-0,035*** (0,011)	0,008*** (0,003)	-0,002*** (0,001)	0,078*** (0,014)	0 0,165	0,059

Panel robustness tests

Model number	TCR (-1)	EX_SYS	EX_SYS_1	EX_SYS_R	EX_SYS_1_R	STOCKM	STOCKM_R	EX_STOCKM	EX_STOCKM_R	EX_STOCKM_2022	EX_STOCKM_2022_R	CPI	UN	NIM	NII_OR	CtI	LA_TA	LOAN_DEPO	LOAN_D	DEPO_D	LN_TA	const	AR (1) AR (2)	Hansen
46	0,772*** (0,045)		-0,001*** (0)			1,028*** (0,251)		-0,133*** (0,024)				-0,015 (0,031)	-0,033** (0,014)	-0,104 (0,131)	-0,001 (0,01)	-0,007 (0,008)	0,025* (0,013)	0,001 (0,003)	-0,036*** (0,011)	0,009*** (0,003)	-0,002*** (0,001)	0,091*** (0,019)	0 0,088	0,2
47	0,765*** (0,048)	0,001 (0,001)					-0,016 (0,156)			-0,12** (0,053)		-0,171*** (0,056)	-0,043*** (0,015)	-0,084 (0,133)	-0,001 (0,01)	-0,007 (0,008)	0,025* (0,014)	0,001 (0,003)	-0,035*** (0,011)	0,008*** (0,003)	-0,002*** (0,001)	0,084*** (0,02)	0 0,096	0,052
48	0,771*** (0,045)				-0,001 (0)	0,76*** (0,212)			-0,12*** (0,022)			-0,044 (0,028)	-0,032** (0,015)	-0,075 (0,132)	-0,001 (0,01)	-0,006 (0,008)	0,025* (0,013)	0,001 (0,003)	-0,036*** (0,011)	0,009*** (0,003)	-0,002*** (0,001)	0,086*** (0,019)	0 0,143	0,216
49	0,765*** (0,048)			0,001** (0,001)			0,085 (0,155)				-0,115** (0,052)	-0,167*** (0,052)	-0,044*** (0,015)	-0,075 (0,131)	-0,001 (0,01)	-0,006 (0,008)	0,025* (0,014)	0,001 (0,003)	-0,035*** (0,011)	0,008*** (0,003)	-0,002*** (0,001)	0,083*** (0,02)	0 0,149	0,07

Online Appendix

Table A1. List of financial institutions included in the study

This table presents the summary information about the financial institutions included in the study. The sample consists of 120 banks from 27 countries, and the sample period spans 2010 through 2022. The table reports the name of the bank (2), its country of origin (1), and its average systemic importance score (3) calculated based on the data provided by the European Banking Authority (2023) and the Bank of England (2023) sourced in the main part of the paper. The last three columns indicate if the bank was included in the empirical estimations: (4) European-Union-wide ΔCoVaR, (5) ΔCoVaR calculated based on the approach of Adrian and Brunnermeier (2016), and (6) panel VAR models (SGMM).

	Country	Bank	Average Systemic Importance Score	European-Union-wide ΔCoVaR	Separate systems ΔCoVaR	Panel VAR models (SGMM)
1	Austria	ERSTE GROUP BANK AG	2337	x	x	x
2	Austria	RAIFFEISEN BANK INTERNATIONAL AG	1714	x	x	x
3	Austria	UNICREDIT BANK AUSTRIA AG	1265			x
4	Austria	BAWAG PSK AG	500	x	x	x
5	Belgium	BNP PARIBAS FORTIS SA	2697			x
6	Belgium	KBC BANK NV	2353	x		x
7	Belgium	ING BELGIUM	1443			x
8	Bulgaria	UNICREDIT BULBANK AD	1880			x
9	Bulgaria	DSK BANK AD	1447			x
10	Bulgaria	FIRST INVESTMENT BANK AD	1195	x		x
11	Bulgaria	UNITED BULGARIAN BANK	892			x
12	Bulgaria	EUROBANK BULGARIA AD	761			x
13	Bulgaria	KBC BANK BULGARIA	714			x
14	Bulgaria	CIBANK JSC	488			x
15	Croatia	ZAGREBACKA BANKA DD	2958	x	x	x
16	Croatia	ERSTE & STEIERMARKISCHE BANK DD	2102			x
17	Croatia	PRIVREDNA BANKA ZAGREB DD	1774	x	x	x
18	Croatia	RAIFFEISENBANK AUSTRIA DD	781			x
19	Croatia	ADDIKO BANK DD ZAGREB	410			x
20	Croatia	HRVATSKA POSTANSKA BANK DD	288	x	x	x
21	Croatia	OTP BANKA DD	558			x
22	Cyprus	BANK OF CYPRUS PUBLIC COMPANY LIMITED	3224			x
23	Cyprus	EUROBANK CYPRUS LTD	1353			x
24	Cyprus	ALPHA BANK CYPRUS LIMITED	409			x
25	Czechia	CESKOSLOVENSKA OBCHODNI BANKA AS	2173			x
26	Czechia	CESKA SPORITELNA AS	1515			x
27	Czechia	KOMERCNI BANKA	1441			x
28	Czechia	UNICREDIT BANK CZECH REPUBLIC AND SLOVAKIA AS	1049			x
29	Czechia	RAIFFEISENBANK AKCIOVA SPOLECNOST	471			x
30	Denmark	DANSKE BANK A/S	5343	x	x	x
31	Denmark	JYSKE BANK A/S	663	x	x	x
32	Denmark	NORDEA KREDIT REALKREDITAKTIESELSKAB	344	x	x	x
33	Estonia	AS LHV PANK	639	x		x
34	Estonia	AS SEB PANK	1986			x
35	Estonia	SWEDBANK AS	3082			x
36	France	BNP PARIBAS	2551	x	x	x
37	France	CREDIT AGRICOLE SA	1793	x	x	x
38	France	SOCIETE GENERALE	1855	x	x	x
39	Germany	DEUTSCHE BANK AG	2638	x	x	x
40	Germany	COMMERZBANK AG	832	x	x	x
41	Germany	UNICREDIT BANK AG	474			x
42	Greece	NATIONAL BANK OF GREECE SA	2674	x	x	x
43	Greece	ALPHA SERVICES AND HOLDINGS SOCIETE ANONYME	2224	x	x	x
44	Greece	PIRAEUS FINANCIAL HOLDINGS SA	2060	x	x	x
45	Greece	EUROBANK ERGASIAS SERVICES AND HOLDINGS SA	2690	x	x	x
46	Hungary	OTP BANK PLC	3063	x		x
47	Hungary	UNICREDIT BANK HUNGARY ZRT	953			x
48	Hungary	K&H BANK ZRT	830			x
49	Hungary	ERSTE BANK HUNGARY ZRT	630			x
50	Hungary	RAIFFEISEN BANK ZRT	590			x
51	Hungary	CIB BANK LTD	427			x
52	Ireland	BARCLAYS BANK IRELAND PLC	941			x
53	Ireland	BANK OF IRELAND	1712	x	x	x

54	Ireland	AIB GROUP PUBLIC LIMITED COMPANY	1262	x	x	x
55	Ireland	ULSTER BANK IRELAND DAC	390			x
56	Italy	BANCA MONTE DEI PASCHI DI SIENA SPA	337	x	x	x
57	Italy	BANCO BPM SPA	330	x	x	x
58	Italy	INTESA SANPAOLO	2604	x	x	x
59	Italy	UNICREDIT SPA	3329	x	x	x
60	Latvia	SWEDBANK AS	2094			x
61	Latvia	AS SEB BANKA	1517			x
62	Lithuania	AB SEB BANKAS	3266			x
63	Lithuania	LUMINOR BANK AB	976			x
64	Lithuania	SWEDBANK AB	2436			x
65	Lithuania	SIAULIU BANKAS	1050	x		x
66	Luxembourg	DEUTSCHE BANK LUXEMBOURG SA	234			x
67	Luxembourg	SOCIETE GENERALE LUXEMBOURG	1124			x
68	Luxembourg	BGL BNP PARIBAS	637			x
69	Luxembourg	JP MORGAN BANK LUXEMBOURG SA	327			x
70	Malta	BANK OF VALLETTA PLC	2709	x	x	x
71	Malta	HSBC BANK MALTA PLC	1283	x	x	x
72	Malta	APS BANK PLC	310	x	x	x
73	Netherlands	ING BANK NV	3997	x	x	x
74	Netherlands	ABN AMRO BANK NV	1524	x	x	x
75	Poland	POWSZECHNA KASA OSZCZEDNOSCI BANK POLSKI SA	1571	x	x	x
76	Poland	SANTANDER BANK POLSKA SA	1090	x	x	x
77	Poland	BANK POLSKA KASA OPIEKI SA	1123	x	x	x
78	Poland	MBANK SA	990	x	x	x
79	Poland	ING BANK SLASKI SA	909	x	x	x
80	Poland	BANK HANDLOWY W WARSZAWIE SA	551	x	x	x
81	Poland	BNP PARIBAS BANK POLSKA SA	485	x	x	x
82	Poland	BANK MILLENNIUM	291	x	x	x
83	Portugal	BANCO COMERCIAL PORTUGUES SA	2109	x	x	x
84	Portugal	BANCO BPI SA	790	x	x	x
85	Portugal	BANCO SANTANDER TOTTA SA	1289			x
86	Portugal	CAIXA ECONOMICA MONTEPIO GERAL	439	x	x	x
87	Romania	TRANSILVANIA BANK	1364	x	x	x
88	Romania	UNICREDIT BANK SA	1373			x
89	Romania	BANCA COMERCIALA ROMANA SA	1448			x
90	Romania	BRD-GROUPE SOCIETE GENERALE SA	1191	x	x	x
91	Romania	RAIFFEISEN BANK SA	947			x
92	Romania	ALPHA BANK ROMANIA	447			x
93	Romania	OTP BANK ROMANIA SA	342			x
94	Romania	GARANTI BANK SA	278			x
95	Slovakia	VSEOBECNA UVEROVA BANKA AS	2278			x
96	Slovakia	SLOVENSKA SPORITEL'NA AS	1784			x
97	Slovakia	TATRA BANKA AS	1383			x
98	Slovakia	CESKOSLOVENSKA OBCHODNA BANKA, AS	1247			x
99	Slovenia	NOVA LJUBLJANSKA BANKA DD	3202	x		x
100	Slovenia	UNICREDIT BANKA SLOVENIJA DD	640			x
101	Slovenia	ABANKA DD	433	x		x
102	Slovenia	NOVA KREDITNA BANKA MARIBOR DD	1324	x		x
103	Slovenia	SKB BANKA DD	612			x
104	Slovenia	BANKA INTESA SANPAOLO DD	528			x
105	Spain	BANCO SANTANDER SA	4282	x	x	x
106	Spain	CAIXABANK SA	903	x	x	x
107	Spain	BANCO BILBAO VIZCAYA ARGENTARIA SA	2069	x	x	x
108	Spain	BANCO DE SABADELL SA	493	x	x	x
109	Sweden	SWEDBANK AB	1518	x	x	x
110	Sweden	SVENSKA HANDELSBANKEN AB	1875	x	x	x
111	Sweden	SKANDINAVISKA ENSKILDA BANKEN AB	2371	x	x	x
112	Sweden	NORDEA HYPOTEK AB (PUBL)	1464	x	x	x
113	United Kingdom	HSBC BANK PLC	1621	x	x	x
114	United Kingdom	BARCLAYS BANK PLC	1143	x	x	x
115	United Kingdom	THE ROYAL BANK OF SCOTLAND PLC	817	x	x	x
116	United Kingdom	LLOYDS BANK PLC	681	x	x	x

117	United Kingdom	JP MORGAN CAPITAL HOLDINGS LIMITED	360			x
118	United Kingdom	STANDARD CHARTERED BANK	275	x	x	x
119	United Kingdom	MERRILL LYNCH INTERNATIONAL	295			x
120	United Kingdom	SANTANDER UK PLC	296			x