Invasion Systemic Risk Premium in the Financial Industry

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Abstract

The Russia-Ukraine conflict exposed the geopolitical risks for businesses in the aggressor country. I estimate the excess systemic risk of having a Russian subsidiary at the outbreak of the war, called *invasion systemic risk premium*, using the data of publicly traded financial companies between 2016 and 2022. I rely on the Generalized Synthetic Control Method (Yiqing 2017), which allows causal inference despite a small sample. Companies owning Russian subsidiaries at the start of the invasion faced a 16.7 basis points invasion systemic risk premium, equivalent to 96 million USD, driven by volatility and interconnectedness. Large firms – especially big banks with high positive returns - are less risky. Firms could only strengthen stability by exiting the Russian market; particularly, non-EU-but-a-NATO-country-managed insurers left Russia. My results show that running a business in an aggressor country is costly even for the least exposed publicly traded financial companies.

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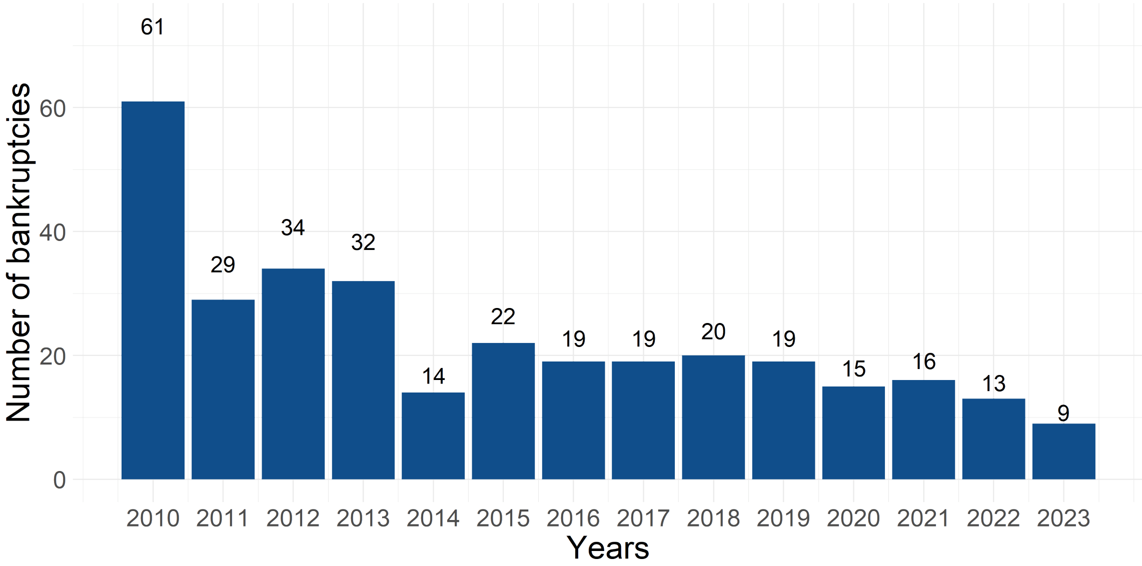
1 Introduction

The 2008 financial crisis started with the downfall of Lehman Brothers, the bank with the largest market capitalization in the United States at the time. The subsequent bankruptcies sent shockwaves through the entire US financial market, culminating in the global financial crisis. Research on systemic risk with an intense focus on preventing the financial ecosystem from future failures increased significantly. Systemic risk quantifies the financial loss in the whole economy induced by the significant decline in the solvency of one or more firms with spillover effects on the whole market and/or to the entire economy (Acemoglu et al. 2015, Eling and Pankoke 2016).[1] The 2008 crisis taught that the spread of bankruptcies, the outdry of liquidity sources, and the fire-sales of stocks might easily collapse the whole financial system, and companies traded on the stock exchange are particularly susceptible to these disruptions since they are easy to trade.

The sudden fall of large banks in the spring of 2023 has reminded investors, supervising authorities, and bank customers of the Lehman moment of the financial industry. The sudden failure of the Silicon Valley Bank and Signature Bank in March of 2023 spilled over to Credit Suisse and First Republic Bank. The upset caused by the insolvency of a Silicon Valley bank was unexpected yet, in hindsight, not completely incomprehensible as it was a medium-sized but deeply interconnected bank. Still, the series of bank insolvencies of 2023 is described as a black swan phenomenon, particularly in the globe's largest economy, the United States. As the frequency of financial firm bankruptcies had decreased in the tranquil years between 2012 and 2020 (see Figure 1), market players became less cautious and focused on return instead of risk. In the better part of the 2010s, owing to the strict banking and insurance regulation that came into force after the 2008 crisis, profit-seeking was difficult in the high growth and low-interest rate environment, and therefore, systemic risk played a minor role in investment and business decisions.

The Russian invasion of Ukraine on 24^{th} February 2022 further impacted the financial system. European (e.g., Germany, France) and Anglo-Saxon countries (i.e., United States of America, United Kingdom, Canada, Australia, and New Zealand), as well as many international companies, imposed sanctions on Russia to punish the country for breaking international law and invading Ukraine. The primary financial sanctions of the countries were

[1] I note that the terms vulnerability, instability, and insolvency are used interchangeably for systemic risk, meaning long-term deficiency of firms to repay obligations.



Source: SP Global Market Intelligence, data were accessed on 20^{th} March, 2023
Note: Bankruptcies in 2023 are reported until 20^{th} of March.

Figure 1: Annual bankruptcies of financial companies in the US between January 2010 and March 2023

aimed at freezing up financial reserves of the Russian National Bank stored outside the Russian Federation, excluding Russian banks from the SWIFT payment system, and prohibiting insuring Russian tankers. Either political pressure (Evenett and Pisani 2023) or concerns for their reputation may have been the driving force behind the decisions of international firms when they chose to scale back their operation in Russia, freeze investments, leave the market, or continue operations (Evenett and Pisani 2023). Due to the changing financial conditions and imposed sanctions on Russia, the financial system's stability changed significantly, but the changes in solvency remained hidden since investors still focused on returns. The return-centered thinking is noted in many academic and business publications related to the war (Sun and Zhang 2022, Abbassi et al. 2022, Evenett and Pisani 2023), disregarding the long-term impact on the systemic stability of the war. Among them, Qureshi et al. (2022) published the only study addressing systemic stability, with a primary emphasis on the country-specific components of geopolitical risk. Therefore, a firm-specific systemic risk analysis is necessary since the changing financial conditions, the war, and the sanctions significantly increased the market uncertainty, which might culminate in further bankruptcies. Systemic risk played a subordinated role in business decisions, which might have increased the interlocking of the financial system making it more vulnerable to failures. The analysis can reasonably start with publicly traded companies that are most exposed to sudden changes since traders can react easily and swiftly to incoming bad news, as happened in the case of the Silicon Valley Bank.

To my knowledge, this is the first study comprehensively analyzing systemic risk dynamics on a one-year horizon concerning Russian aggression. It benefits from utilizing the balance sheet data for 2022, measures financial interconnectedness, and evaluates the effectiveness of financial firms' sanctions. The thesis shows the fourfold effects of the Russian invasion on systemic risk: (i) it measures the *invasion systemic risk premium* expressed in Marginal Expected Shortfall using Generalized Synthetic Control Method (Yiqing 2017) between 2016 and 2022, (ii) determines contributing factors of the *invasion systemic risk premium*, (iii) quantifies the impact of corporate sanctions to systemic risk, and (iv) identifies the main firm characteristics determined the "levied" sanctions. The main research question is whether publicly traded financial companies owning a Russian subsidiary have a higher systemic risk called *invasion systemic risk premium*. I found a significant 16.7 basis points invasion systemic risk premium of publicly traded financial firms with Russian exposure. The main drivers of the Marginal Expected Shortfall of firms were volatility and clustering coefficient, while market capitalization, deposits, and skewness reduced systemic risk. Exiting the Russian market was the only significant corporate sanction that reduced systemic risk. Almost all headquarters locations for the studied countries decreased Marginal Expected Shortfall compared to the United States of America. Headquarters in NATO member states signaled security by reducing the systemic risk of their residing companies. Insurance companies managed from non-EU-but-NATO-member states tended to leave Russia rather than stay on the market. Finally, I highlight that the results may depend on the used systemic risk variable and the length of the pre-treatment period. The analysis was replicated using ΔCoVaR, resulting in an insignificant systemic risk premium. The different outcome might be a consequence of the scale invariance of ΔCoVaR or the choice of the system variables.

The structure of the thesis is organized as follows. Firstly, it reflects on the literature from two perspectives: first, section 2.1 shows the deficiencies of empirical studies that measure (cumulative) abnormal returns and examines the possible driving factors of abnormal returns since systemic risk factors have not been analyzed in the context of the Russian invasion. In addition, section 2.2 examines further covariates related to geopolitical risk, like balance sheet variables and geographical characteristics, and provides possible ways for the management board to reduce the impact of risk spillovers. This approach allows for incorporating the most relevant variables in the empirical analysis to explain *invasion systemic risk premium*. Chapter 3 describes the used dataset and variables, while Chapter 4 summarizes the calculation of Marginal Expected Shortfall and discusses the Generalized Synthetic Control Method. The research design is described in Chapter 5, while Chapter 6 presents the GSCM results and cross-sectional regression outcomes. The methodology's limitations are mentioned in Chapter 7 and Chapter 8 concludes and formulates recommendations for the direction of future research.

2 Literature review

Section 2.1 highlights that systemic risk analysis has been largely ignored in the Russia-Ukraine-war-related literature, especially firm-level systemic risk reports and longer-term impacts of the military conflict are missing. Section 2.2 examines the relationship between geopolitical risk and firm characteristics to identify possible drivers of systemic risk and describes geopolitical risk transmission via balance sheet variables.

2.1 Empirical literature

In this section, I first reflect on the current research topics related to the Russia-Ukraine war and show that systemic risk-related research focusing on firm-specific factors is a minor stream of the literature. Secondly, I collect the driving factors of (cumulative) abnormal returns, possibly explaining systemic risk. The Russia-Ukraine war-related empirical literature has three main topics. Most studies analyze the (cumulative) abnormal returns closely after the start of the *special military operation*. The second stream of literature reflects the risk spillovers among different assets and the causal relationship between markets. Only one study is related to corporate sanctions.

The first stream of the literature confirmed the existence of (cumulative) abnormal returns by analyzing country-, sector/index-, and firm-level data. The standard methodology of abnormal return analysis is the event-study approach and sometimes the OLS regression. These studies aimed to identify the determining factors. The articles differ in the used dataset, the target assets (equities, commodities, (crypto)currencies, and indices), the time horizon, and the granularity of the analysis (country, sector/index, or firm level).

Research analyzing country-level data detected (cumulative) abnormal returns around the time of the invasion (Boubaker et al. 2022, Lo et al. 2022, Boungou and Yatié 2022, Kumari et al. 2023). The authors focused on the first three-month daily effect of the Russian aggression in 2022, except Kumari et al. (2023), whose sample started at the beginning of 2021. They concluded that the negative abnormal returns closely around the time of the invasion (24^{th} February 2022). But explanatory variables differ: Boungou and Yatié (2022) applied a war proxy expressed by Google searches to war-related expressions like (Russia, Ukraine, war, Vladimir, and Putin), while Lo et al. (2022) controlled Russian trade dependency. They found a decrease in index returns when the dependence from Russia exceeded 20%. Boubaker et al. (2022) had a similar conclusion, GDP-scaled trade negatively affected abnormal returns, while NATO members increased average returns. Hence market expectations of future returns rose parallel with the increasing military expenses. The positive impact of NATO membership was confirmed by Kumari et al. (2023). They found a positive effect of developed country dummies but a negative relationship between sanctions and export on the abnormal returns.

Articles focusing on commodities and currencies reported significant abnormal returns of oil and gas indices, and the US dollar appreciated against many European currencies. Russia's economy particularly relies on fossil energy source export (oil, gas, coal, and refined products), Umar, Riaz and Yousaf (2022) identified that the gas and oil index have had sizeable abnormal returns on the starting day of the war using 10 clean energy indexes, 6 conventional energy source indexes, and 10 metal index data from 2^{nd} September 2021, through 25^{th} March 2022. The war impacted both the commodity market and the exchange rate of global currencies. Chortane and Pandey (2022) concluded that European currencies were depreciated against the dollar, primarily the Russian rouble, the Czech koruna, and the Polish zloty, Pacific currencies appreciated significantly, and the currencies of the Middle East and Africa are insignificant (Chortane and Pandey 2022, p.1). Sanctions weakened the Russian rouble against the US dollar, and the proximity to the conflict area increased the course of currencies. Nevertheless, pegging the rouble with gold strengthens the rouble. Not only the traditional but the cryptocurrencies were affected by the war. Theiri et al. (2022) found an increased liquidity level in Bitcoin and Ethereum within two days around the invasion, but it returned to the pre-event level after that (Theiri et al. 2022, p.59).

The corporate-level abnormal returns were found in several industries and countries around 24^{th} February 2022, but the driving factors of abnormal returns depended on the sample selection. Abbassi et al. (2022), Sun and Zhang (2022), Ahmed et al. (2022) and Federle and Sehn (2022) applied an event-study approach to identify abnormal returns around the invasion. Abbassi et al. (2022), Sun and Zhang (2022), Ahmed et al. (2022) relied on one year of daily data started in the first month of 2021 and ended in March 2022. Drivers of abnormal returns are risk exposure and trade dependence (Abbassi et al. 2022). On the other hand, a higher book-to-market ratio made companies more vulnerable to shocks. Small firms overperformed - in returns – the large ones in the G7 countries. Geopolitical risk and trade dependence also drove returns to negative, but US and French firms were unaffected. Sun and Zhang (2022) showed geopolitical, economic, institutional, humanitarian, industrial, and also firm-related factors to explain abnormal returns. The authors found a positive effect of corporate sanctions on the abnormal and cumulative abnormal returns of 140 firms. The sanctions were measured ordinally, which hid the difference in the severity of decisions. Federle and Sehn (2022) and Ahmed et al. (2022) considered distance from the war zone a significant explanatory variable. Federle and Sehn (2022) found that additional 1,000 kilometers increased returns by 1.1 percentage points. Ahmed et al. (2022) identified the highest losses in the financial industry, suggesting that this sector had a distinguished role and worth for a more detailed analysis from other perspectives, like systemic stability.

The second stream of the literature is related to risk transmission and the causal relationship between asset classes. These studies highlighted that Geopolitical Risk (GPR) Index affected equity, bond, and commodity markets, energy, consumer, and technology sectors, and the United States, Canada, China, and Brazil were the main shock recipients. Sanctions were found to impact country-level systemic risk. The second stream of studies mostly compares index performance, asset classes, and currencies. One part considered a short-term risk transmission using a few-month time window around the invasion, and others extended the scope to a one-year environment of the war. The last day in the sample in (Umar et al. 2023)'s research was 5^{th} July 2022. The commodity market was analyzed by Alam et al. (2022), Wang et al. (2022) and Umar, Bossman, Choi and Teplova (2022). Alam et al. (2022) and Wang et al. (2022) applied the TVP-VAR combined with the Diebold-Yilmaz spillover index, while Wang et al. (2022) and Umar, Bossman, Choi and Teplova (2022) gauged Granger-causality among seven Russian, European bond, equity, and commodity indices and the Geopolitical Risk (GPR) Index. Alam et al. (2022) identified gold and silver as shock receivers. All commodity markets became highly interconnected due to the war. The US, Canada, China, and Brazil were shock recipients, while the European countries were net transmitters of shocks. Wang et al. (2022) found that crude oil transmitted return spillovers, while wheat and soybeans were found as net receivers of shocks. Costola and Lorusso (2022) identified Russian oil and gas sectors as the main risk contributors even before the war (between 2005 and 2020). Umar, Bossman, Choi and Teplova (2022) applied the generalized Granger-causality in the quantile method and found that GPR leads to asset returns in tranquil times. Umar et al. (2023) concluded that short equity indices are beneficial to manage the very-short term risk implied by the war. Moreover, shorted stocks moved together with Geopolitical Risk Index — the energy, consumer, and technology sectors were detected as geopolitical risk-takers. Aliu et al. (2023) studied the risk transmission on the currency market between five exchange rates using daily series between 1^{st} November 2021 to 1^{st} May 2022 and detected that EUR/RUB significantly influenced the Euro devaluation. Qureshi et al. (2022) published the only study reflecting the systemic risk issues of the Russia-Ukraine war. Daily data of stock indices from eight countries (Russia, Ukraine, France, Germany, Italy, the UK, the USA, and China) was analyzed between 1^{st} January 2021 to 11^{th} March 2022. Sanctions were found to cause systemic risk spillovers to Europe and the USA, but China was non-effected by them.

Only one report belongs to the third stream of the literature. Evenett and Pisani (2023) published a detailed descriptive analysis of corporate sanctions. The authors focused on the geographical distribution of firms' reactions. The authors highlighted that 8.5% of all European and G7 firms operated in Russia exited the market, but the study leaves space for causal inference of corporate sanctions since they only hypothesize the relationship of the country of origin and the taken sanctions.

In conclusion, empirical articles in the relevant literature found significant abnormal returns around the time of the invasion and detected many driving forces of abnormal returns, like trade exposure, proximity from the conflict zone, financial characteristics, and return moments. The studies did not reflect on the changes in the second half of 2022 and disregarded the role of the market network structure amplifying the shocks during the 2008 crisis. These issues can be resolved by considering balance sheet data and network characteristics for an extended period. The financial sector suffered the highest losses in return (Ahmed et al. 2022), and its stability might have been impacted the most by the war's spillover effects, making systemic risk research of this industry relevant. The impact of sanctions was analyzed either in a simplified way (Sun and Zhang 2022) or only a structured overview was provided (Evenett and Pisani 2023). Therefore, a comprehensive analysis of corporate sanctions and their driving forces is still missing from the literature, and I aim to fill this gap.

2.2 Geopolitical risk

This section discusses the firm-specific factors affected by geopolitical risk. The highlighted articles reflect on firm-specific characteristics that might determine the systemic stability of companies. Historical studies on geopolitical risk were considered since the firm-specific factors related to invasion-induced instability are missing from the literature. Geopolitical risk is defined "as the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations" (Caldara and Iacoviell 2022, p.1596). Geopolitical risk is measured by Caldara and Iacoviell (2022)'s Geopolitical Risk Index (GPR). GPR was extracted from 25 million news published between 1900 and 2020. The empirical studies incorporated the GPR index for causal inference to detect the impact of geopolitical risk on corporate characteristics.

The relationship between geopolitical risk and insurance premium was ambiguous, while bank size strengthened solvency. Lee and Lee (2020) revealed a causal relationship, based on data of BRICS countries from 1985 to 2017, between GPR and insurance premiums in Brazil and South Africa and lower-tail causality between real output, insurance premiums, and GPR in Russia. In addition, Hemrit and Nakhli (2021) detected an asymmetric and non-linear relationship between GPR and insurance premiums in 19 countries except for India between 2000 and 2019, and the effect of geopolitical risk was more influential in the long-run. The demand for insurance became stronger, parallel with increasing geopolitical risk, but GPR shocks decreased insurance premiums in Venezuela, South Africa, and Mexico. Nevertheless, insurance services became more expensive in China due to geopolitical shocks. The adverse reaction of premiums made the relationship between GPR and insurance premiums ambiguous. At the same time, the banking industry was analyzed by Phan et al. (2022), who concluded that bank size and the available capital reduced the destabilizing effect of geopolitical risk.

Geopolitical risk lowered investments. Wang et al. (2019)'s regression analysis on 9,088 firms' quarterly data between 1987 Q1 to 2016 Q3 found a negative relationship between GPR and investments. Lee and Lee (2020) also confirmed that geopolitical risk lowers investments based on the data of 10,695 firms in nine Asian countries from 1995 to 2018 using the two-stage OLS methodology. The results were highly significant in Russia and China and less in India and Turkey.

Adra et al. (2023) found that geopolitical risk-affected firms spent less on share repurchase, analyzing 12,883 US firms between 1985 and 2019. At the same time, cash dividends were unimpacted. Lee and Wang (2021) drew the same conclusion as Adra et al. (2023). Namely, they found that non-financial Chinese manufacturing firms tended to save more cash facing geopolitical risk, especially during the China-United States trade war. Lee and Lee (2020) concluded that firms from nine Asian countries were more resistant to the shocks by increasing their cash holding. Generally, financially constrained firms accumulate cash as a reserve against future shocks.

The empirical studies in the related stream of the literature concluded that geopolitical risk lowered corporate investments and made payout policy more conservative, but cash dividends remained unimpacted. At the same time, cash reserves increased. GPR diversely affected insurance premiums, while the size of the banks and capital increased stability. The Russian invasion-related empirical research and the geopolitical risk-focused studies have one primary benefit: they allow for incorporating relevant covariates in the Generalized Synthetic Control framework and the cross-sectional analysis of corporate sanctions.

3 Data

I compare publicly traded financial companies from the banking, insurance, and payment sectors. The classification is made based on www.leave-russia.org website listing companies with exposure to the Russian market. Only publicly traded firms are considered since firm-level, reliable data are available for exchange-traded companies. Publicly traded financial firms are usually large concerns with numerous subsidiaries; consequently, the available data reflects the changes in the whole conglomerate. The financial sector is analyzed, which was particularly hit by the traders after the war (Ahmed et al. 2022), and this sector is primarily involved in the sanctions against Russia. The outcome variable is Marginal Expected Shortfall (MES), which measures the systemic risk of firms. MES is preferred in this analysis for three reasons: (i) it is easy to interpret, (ii) it measures the systemic risk changes on an absolute scale, (iii) MES is related to the extreme returns, which supports utilizing the conclusions of the Russian war-related empirical papers. The calculation of MES is discussed in section 4.1. Another fundamental and widespread systemic risk measure is ΔCoVaR. I implement MES for three reasons. Once the interpretation of ΔCoVaR is less intuitive, systemic risk changes are compared to the median firm's risk exposure. Therefore, it measures systemic risk on a relative scale making the outcome resistant to the shifts of the loss distribution. Thirdly, the estimation of ΔCoVaR is based on so-called state variables (please refer to Appendix A and Appendix B), of which choice might be arbitrary. As a robustness test, results for ΔCoVaR are reported in Appendix F.

The thesis has two parts. In the first part, firms are classified as to whether they had a Russian subsidiary at the time of the invasion (24^{th} February 2022). The treatment group owned a subsidiary, while the control group did not. Data frequency is annual since the balance sheet variables are published annually. Daily data was only used to calculate specific measures. While in the second part, I only focus on treated companies and investigate the relationship between the management board's actions and systemic risk. I also analyze the determining factors of companies' decisions considering cross-sectional data for 2022.

The data were accessed from the Refinitiv Datastream database between 1^{st} January 2016 and 31^{st} December 2022. The dataset was cleaned and imputed, meaning that the missing values were interpolated using the weighted average of neighboring observations putting the higher weight on the closer data point.[2] The treatment group was characterized by www.leave-russia.org, a project of the Kyviv University. All data of publicly traded financial companies were included in the dataset available from Datastream. The pool of the control group was selected based on market capitalization and country of origin. I tried to include as many companies as possible from the same countries as the treated firms with the highest market capitalization since treated companies are the most valuable financial firms. After data cleaning and imputation, 119 companies remained in the treatment group and 151 in the control group.

Five types of variables were used for the analysis:

- Balance sheet variables: ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio,

[2] $X_{i,t} = w_{i,t-k} * X_{i,t-k} + w_{i,t+l} * X_{i,t+l}$, where $w_{i,t-k} = \frac{l}{l+k}$ and $w_{i,t+l} = \frac{k}{l+k}$. i denotes the firm's index, t the time, $t+l$, and $t-k$ are the closest available dates, and X is the general notation of a variable.

revenues, and operating expenses. Nominal amounts are downloaded and reported in thousand dollars.

- Log return and return moments: volatility and skewness.
- Network measures: clustering coefficient and betweenness centrality.
- Geographical characteristics: EU membership, NATO membership, Anglo-Saxon countries[3], country of the firms' headquarters, and ln(distance of the headquarters from Ukraine).
- Corporate sanctions to the war. For treated companies, the board decisions were scraped from www.leave-russia.org (continue operations, exit completed, suspension, withdrawal, pausing investments, and scaling back).

The last two categories, geographical variables and corporate sanctions were only used for the cross-sectional analysis.

Balance sheet variables were selected based on the empirical literature (section 2.1 and section 2.2) and data availability. They reflect on the corporate characteristics, including the decision of the management boards on debt structure, dividend policy, the efficiency of reducing operating expenses, etc. All amounts were converted to US dollars. Positive balance sheet variables were transformed with logarithm, more precisely Ln(X)=Ln(1+X), since the IPO of some companies happened during the analyzed period and the data were not reported earlier. Revenues and operating expenses could be negative. For instance, a bank's income is negative if the loans are not going to be paid back, and they have to deduct the loss. Operating expenses might be negative for insurance companies. For example, in the case of car insurance, when a loss occurs, the experts judge the amount of the reparation. If they overestimate the costs, the excess money, stored in reserves, is freed up, called regress. Especially for large claims, the amount can be significant, resulting in negative operating expenses. Volatility and skewness were calculated on annual frequency based on daily log returns; they reflect the attitudes of investors. Investors tended to sell many Central-European stocks after the Russian invasion since they tried to react to the war, but the Russian stock exchange was closed. The increasing fear of the investors rose volatility, and significant losses occurred. Network measures are included to reflect the interconnectedness of the financial

[3]Anglo-Saxon countries are the United States of America, the United Kingdom, Australia, Canada, and New Zealand. (No firms are included in the sample from New Zealand.). Anglo-Saxon countries, except New Zealand, are highly developed and have deeply integrated intelligence systems, which might make these nations special considering geopolitical risks.

system. These variables also serve as a proxy for non-published trading relationships, which might cause risk spillovers and further losses. The financial network characteristics were derived from annual Granger-causality networks following Billio et al. (2012) estimated using daily log returns. The (local) clustering coefficient is calculated as $C_i = \frac{n_\Delta(i)}{k_i(k_i-1)/2}$, where $n_\Delta(i)$ denotes the number of triangles including node i. K_i expresses the degree of a node. Intuitively, the clustering coefficient denotes the probability that a node is connected to its neighbors (Barabási 2016, p.26). Betweenness centrality measures the number of the shortest paths going through node i normalized by the number of all shortest paths expressed with the formula $C_B(i) = \sum_{i \neq k \neq l} \frac{n_{kl}(i)}{n_{kl}}$ (Barabási 2016, p.14). The proximity to war is expressed in the natural logarithm of the distance between corporate headquarters and Ukraine. The geographical distance provides a weighted measure to quantify the influence of geopolitical risk. Country distance data from Ukraine are calculated based on CEPII's data. EU membership has a non-weighted geographical aspect since many EU member states are closely located to the conflict region, and the European integration has almost a consensus condemning the war and introducing financial sanctions against Russia. NATO (North Atlantic Treaty Organization) membership reflects on the military escalation of the invasion and aims to test whether NATO membership influences not only the abnormal returns but also systemic risk. Anglo-Saxon countries (United States of America, United Kingdom, Canada, New Zealand, and Australia) were leading the introduction of sanctions against Russia; the dummy variable reflects their relationship to the conflict and its consequences to systemic risk.

4 Methodology

This chapter introduces the methodology of Marginal Expected Shortfall (MES) and describes the Generalized Synthetic Control Method.

4.1 Marginal Expected Shortfall (MES)

The Marginal Expected Shortfall (MES) is a widely used systemic risk measure that quantifies the average returns in the lower 5% tail of the distribution (Acharya et al. 2017).[4] The Marginal Expected Shortfall is based on the ideas of expected shortfall and Value-at-Risk

[4]The description of the Marginal Expected Shortfall is based on Acharya et al. (2017), but the formulation was developed for the author's MSc thesis (Reizinger 2020, pp.97-98).

(VaR). Company i's exposure to the market (r_M) is expressed by the Marginal Expected Shortfall (1), q is usually set to 5%.

$$MES_i(q) = \mathbf{E}(r_M | r_i \leq -VaR_i(q)) \tag{1}$$

The Marginal Expected Shortfall is estimated the following way (Acharya et al. 2012, 2017, Brownlees and Engle 2017). Equation (2) denotes the stochastic process of returns.

$$\begin{aligned} r_{M,t} &= \sigma_{M,t}\epsilon_{M,t,1} \\ r_{M,t} &= \sigma_{i,t}\rho_{i,t}\epsilon_{M,t,2} + \sigma_{M,t}\sqrt{(1-\rho_{i,t}^2)}\epsilon_{j,t,2} \\ \left(\epsilon_{M,t,1}, \epsilon_{i,t,2}\right) &\sim H, \end{aligned} \tag{2}$$

where $r_{i,t}$ is the time series of firm i's return and $r_{M,t}$ is the market return time series (e.g., $SP500$). $\sigma_{i,t}$ is the i^{th} company's conditional volatility, while $\sigma_{M,t}$ is the conditional volatility of the market. $\rho_{i,t}$ denotes the conditional correlation between firm i and the market.

H, the error term is described by an i.i.d. bivariate process with zero mean and zero covariance, and unit variance $\left(\left(\epsilon_{M,t,1}, \epsilon_{j,t,2}\right)\right)$. ($\mathbb{E}(\epsilon_{i,t,k}) = 0$, $Var(\epsilon_{i,t,k}) = 1$, i$\in$ j, M and k $\in$ $1,2)$. The error terms are uncorrelated, but independence cannot generally be assumed.

The one-period-ahead process of the Marginal Expected Shortfall is described in equation (3):

$$\begin{aligned} MES_{i,q,t-1}(1) &= \mathbb{E}_{t-1}(R_{i,t} | r_{M,t} \leq -VaR_M(q)) = \sigma_{i,t}\mathbb{E}_{t-1}\left(\rho_{i,t}\epsilon_{M,t,1} + \sqrt{(1-\rho_{i,t})^2}\epsilon_{i,t,2} \middle| \frac{-VaR_M(q)}{\sigma_{M,t}}\right) \\ &= \sigma_{i,t}\rho_{i,t}\mathbb{E}_{t-1}\left(\epsilon_{M,t,1} \middle| \frac{-VaR_M(q)}{\sigma_{M,t}}\right) + \sigma_{i,t}\sqrt{(1-\rho_{i,t})^2}\mathbb{E}_{t-1}\left(\epsilon_{i,t,2} \middle| \frac{-VaR_M(q)}{\sigma_{M,t}}\right), \end{aligned} \tag{3}$$

where the standard deviations of firm i and the market ($\sigma_{i,t}$, $\sigma_{M,t}$) are estimated by a GJR-GARCH model. $\rho_{i,t}$ is calculated via a dynamical conditional correlation model.

4.2 Generalized Synthetic Control Method (GSCM)

The Difference-in-Differences (DiD) method is usually used to compare the treatment and control groups and to make causal inferences with panel data. But DiD assumes that the treatment and the control group co-move before the treatment occurs (called parallel trend assumption), which is challenging to satisfy. On the other hand, auto-selection and a strong imbalance of covariates do not allow using this framework. The Synthetic Control Method (SCM) proposed by Abadie and Gardeazabal (2003) could be a plausible choice. SCM makes it possible to avoid the arbitrary choice of the control group (Abadie and Gardeazabal 2003, Abadie et al. 2010) and releases the parallel trend assumption. The Synthetic Control Method combined with matching procedures could resolve the issue of imbalanced variables, but it may be inappropriate for causal inference. Since matching only works for observable variables but misses unobservables, it could result in biased coefficient estimates (Abadie 2021). Abadie (2021) proved that under certain conditions, factor models provide unbiased estimates applicable for causal inference. For instance, Yiqing (2017)'s Generalized Synthetic Control Method benefits from the factor model approach since it is based on the Interactive Fixed Effects model (a factor model). This makes the framework appropriate for coefficient estimates and quantifying the average treatment effect on the treated. The author emphasized the four main advantages as follows (Yiqing 2017, p.57,p.59):

1. The treatment can be correlated with (unobserved) variables and time heterogeneities.
2. The methodology can incorporate multiple treated observations.
3. The procedure includes cross-validation to select the optimal number of factors for the Interactive Fixed Effect model.
4. The methodology calculates standard errors and confidence intervals for causal inference. The parametric estimation procedure is designed for small sample sizes to produce robust results. Moreover, all units of the control group are used for bootstrapping. Consequently, this approach is more efficient than the synthetic control method with matching.

The main idea of the Synthetic Control Method is based on a donor pool. It implements a data-driven approach to select the control group by weighting the observations. The generalized framework creates synthetic counterfactuals for all treated units. (Please refer to Appendix C for the assumptions, detailed estimation, and causal inference.) The incorporated Interactive Fixed Effects (IFE) module assures that auto-selection (the correlation of the treatment with some covariates) and omitted, time-dependent factors do not cause problems during the estimation. The procedure estimates the Interactive Fixed Effects model, which was introduced by Bai (2009) using individual factor loadings (fixed effects) interacted with time-varying coefficients. The main innovation of the Generalized Synthetic Control Method is that it provides parametric bootstrapped standard errors and confidence intervals for causal inference. (6) denotes the estimation equation of synthetic counterfactuals of treated units based on the Interactive Fixed Effect framework, see equation in (4).

$$Y_{it} = \delta_{it} D_{it} + X'_{it}\beta + \lambda'_i f_t + \sum_{k=1}^{T} ø_k \tau_k + \omega_i + \varepsilon_{it}, \tag{4}$$

where D_{it} denotes the treatment dummy, defined in (5)

$$D_{it} = \begin{cases} 1, \text{ if } i \in \mathscr{T} \text{ and } t > T_0, \\ 0 \text{ otherwise.} \end{cases} \tag{5}$$

δ_{it} represents the heterogenous treatment effect of unit i at time t. $X_{i,t}$ is the observed covariate vector with β a coefficient vector. f_t denotes the factors with λ_i loadings. τ_k and ω_i are the time and individual fixed effects with $ø_k$ coefficients. Finally, ε_{it} is a zero-mean innovation for unit i at time t. Based on (5), the synthetic counterfactual is estimated in (6).

$$\widehat{Y}_{it}(0) = X'_{it}\widehat{\beta} + \widehat{\lambda}'_{it}\widehat{f}_t + \sum_{k=1}^{T} \widehat{ø_k}\tau_k + \widehat{\omega_i},\ i \in \mathscr{T}, t > T_0. \tag{6}$$

N_{tr} is the number of the treatment units, T_0 is the time of the treatment. $\widehat{\beta}$, $\widehat{\lambda}_{it}$, and $\widehat{f}_t$ are the estimated coefficients, loadings and time-variant factors. Factor selection is carried out via leave-one-out cross-validation. The Average Treatment Effect on Treated is formulated in (7), calculating the difference between treated units and their synthetic counterfactuals.

$$\widehat{ATT}_t = \frac{1}{N_{tr}} \sum_{i \in \mathscr{T}} \left(Y_{it}(1) - \widehat{Y}_{it}(0)\right) \text{ for } t > T_0. \tag{7}$$

5 Research design

The aim of this thesis is two-fold. Once, I compare publicly traded financial companies owning Russian subsidiaries (treatment) and ones with having no subsidiaries. In other words, companies with and without geographical exposure to Russia (having employees, offices, etc., in Russia) are contrasted. Since a randomized control trial is not possible, Difference-in-Differences could be an appropriate approach. Nevertheless, it has the parallel trend assumption, the covariates should be balanced, and the treatment should be independent of the covariates. If the independence criterion fails, auto-selection exists, and the results are unreliable. section 6.1 tests the auto-selection. The analysis finds that the treatment depends on some covariates, and the variables are quite imbalanced. Consequently, the Difference-in-Differences framework is inadequate. Nevertheless, Yiqing (2017) proposed the Generalized Synthetic Control Method (GSCM), which allows the dependence of treatment on covariates, and naturally, by creating a synthetic control group, the imbalance of covariates is reduced as much as possible. Moreover, the treatment group can include multiple treatment units, and GSCM is applicable for causal inference calculating bootstrapped standard errors.[5] The pre-treatment period lasts from 2016 to 2021, and the year of the treatment is 2022.

I use one of the most widespread gauge, Marginal Expected Shortfall (MES), as an outcome variable to express the risk exposure of companies. The results are reported for ΔCoVaR in Appendix F as a robustness test. For Marginal Expected Shortfall and ΔCoVaR, the lower 5% of the losses is considered a threshold ($q = 5\%$). Systemic risk measures are estimated from daily observations to indicate the short-term changes in the system. The annual averages of the systemic risk measures are calculated to match the annual frequency of the dataset with the systemic risk measures.

Secondly, using linear regression, I analyze the impact of management decisions on the systemic risk of treated companies on annual cross-sectional data of 2022. Namely, I test whether the reaction to the invasion, such as suspending operations, stopping investments, leaving the market, etc., influenced the systemic risk of firms. Furthermore, I examine which corporate characteristics influenced the management decisions to the war by applying multinomial logistic regression. Geographical fixed effects are included in the models since they might indicate country-specific or integration-related risks. Section 6.1 tests the auto-selection in the sample presenting the panel probit regression results and the covariate (im)balance. section 6.2 summarizes the GSCM results, and section 6.3 presents the cross-sectional results on the treatment group.

6 Results

6.1 Pre-testing the data and the assumptions of GSCM

This section examines two reasons why the Difference-in-Differences methodology is inappropriate for estimating the invasion systemic risk premium. Moreover, the parallel trend

[5]The size of the bootstrap sample was set to 1000.

assumption and the Generalized Synthetic Control Method's conditions are tested.

The first reason for the inaccuracy of the Difference-in-Differences is the imbalance of covariates. Table A.2, Table A.3, and Table A.4 summarize the results of annual pairwise t-tests of the covariates where the treatment and the control groups were compared. The difference between ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), debt-to-capital ratio, revenue, and operating expenses are significant for all years. In contrast, return on assets, price-to-book ratio, and betweenness centrality were balanced in the two groups. Average volatility and clustering coefficient were statistically equivalent in the two clusters only in one year. Finally, dividend yield, return, and skewness were balanced in some years, while in others, they differed. Therefore, seven variables from fifteen significantly differed in all years, suggesting a solid imbalance in covariates which motivates applying the synthetic control method (SCM).

Secondly, auto-selection was detected in the sample. The treatment (=a company had a Russian subsidiary at the time of the invasion) depends on some covariates. Table A.1 shows the marginal effects at the mean of the panel probit regression, which concludes that the treatment is not independent of the other variables, but different error clustering[6] results in distinct significant explanatory variables. Except in the case of Anglo-Saxon country-level error clustering, revenue causes auto-selection in the sample. In addition, I tested the parallel trend assumption. The p-value of the test equals 5.3%, meaning that the null hypothesis cannot be rejected at 5% significance level. Consequently, the parallel trend hypothesis is met, but the substantial imbalance of covariates and the auto-selection in the sample support using the Generalized Synthetic Control method to the Difference-in-Differences framework.

Finally, the conditions of the Generalized Synthetic Control Method are examined. The Generalized Synthetic Control method lies on four assumptions: (i) GSCM assumes a linear functional form described in (4), (ii) strict exogeneity assumption holds, (iii) weak serial correlation of the error term is allowed, (iv) general regulatory conditions are met, and (v) the cross-sectional error term is homoscedastic. The functional form of the relationship between the outcome and the covariates is satisfied by assumption. Strict exogeneity is fulfilled due to the Interactive Fixed Effects Model. Namely, $\mathbb{E}\left(\varepsilon_{it}|D_{it}, x_{it}, \lambda_i, f_t\right) = \mathbb{E}\left(\varepsilon_{it}|x_{it}, \lambda_i, f_t\right)$ equality holds from two reasons. If the treatment depends on some observed variables, the

[6]The results are reported as sensitivity tests with distinct error clustering (no error clustering, clustering on EU-member level, Anglo-Saxon country-level clustering, NATO-level clustering, country-level clustering, and robust standard errors).

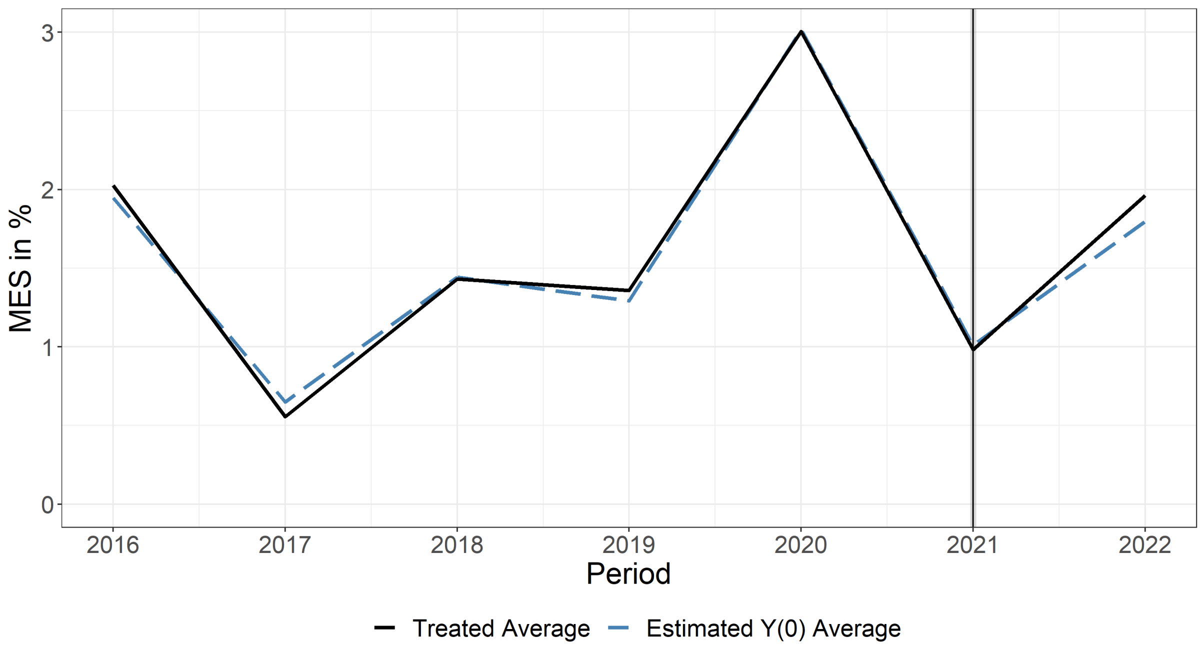
treatment can be excluded from the conditions using the law of iterated expectations. (Covariates incorporate all information from the treatment.) Conversely, if there is an omitted variable, the factors control that information. I tested the serial correlation of the residuals and found no significant autocorrelation of the error terms for lags $=1,2,\ldots,7$ at 5% significance level. When the test was replicated at 10% significance level, only in ten cases was autocorrelation detected. Therefore, the third condition is met. The fourth assumption expects to fulfill regularity conditions, like bounded moments. The sample is finite; consequently, the moments are bounded. Finally, a cross-sectionally homoscedastic error term is expected. I ran the White heteroscedasticity test on the residuals annually (White 1980). The tests concluded that the error term is homoscedastic at 5% significance level in all years. All conditions are fulfilled by construction (i) or testing (ii-v). Therefore the Generalized Synthetic Control Method is applicable.

6.2 Generalized Synthetic Control Method (GSCM)

This section presents the results of the Generalized Synthetic Control Method, namely the coefficient estimates based on the Interactive Fixed Effect Model and the Average Treatment Effect on the Treated. Figure 2 shows the co-movement of the average systemic risk variable in the treatment and synthetic control groups. The average Marginal Expected Shortfall for the treatment, control, and synthetic control groups are summarized in Table 1. The counterfactual estimated by the Generalized Synthetic Control Method seems appropriate since it could mostly balance the differences in the Marginal Expected Shortfall.

	Average MES (in %)		
Year	**Treatment**	**Synthetic Control**	**Control**
2016	2.027	1.946	1.633
2017	0.554	0.650	0.675
2018	1.432	1.442	1.350
2019	1.359	1.293	1.107
2020	3.004	3.017	2.987
2021	0.981	1.010	0.956
2022	1.962	1.796	1.586

Table 1: Annual averages of Marginal Expected Shortfall in the treatment, control, and synthetic control groups calculated by the Generalized Synthetic Control Method



Note: Estimated Y(0) is the synthetic counterfactual.

Figure 2: Marginal Expected Shortfall's dynamics in the treatment and synthetic control groups

Table 2 summarizes the coefficient estimates and confidence intervals based on Interactive Fixed Effect Model ($Y_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \sum_{k=1}^{T} \o_k \tau_k + \omega_i + \varepsilon_{it}$, only the β coefficients are reported. The most influential factor affecting systemic risk is stock price volatility. Unit rise of the volatility increases Marginal Expected Shortfall (MES) of company i at time t - on average, ceteris paribus - by more than 50%-points, which clearly shows that uncertainty was the main driver of systemic risk in the last seven years. Not surprisingly, the clustering coefficient amplifies systemic risk, meaning that if a firm is more likely to be connected to its neighbors, that propagates systemic risk; thus, shock spillovers are more likely in a more integrated financial system. The impact of the network structure is smaller than volatility, but the predicted Marginal Expected Shortfall of a given company at time t is larger by 3.8%-points if the clustering coefficient increases by 1%-point. Other variables reduce MES, like 1% increase of the market capitalization decreased the predicted systemic risk of company i at time t by 0.058%-points, ceteris paribus. The result confirms Phan et al. (2022)'s finding that larger firms are less affected by geopolitical risk.

Deposits can be interpreted as a weighted proxy for banks since neither payment companies nor insurers are allowed to collect deposits. GSCM found that banks were more resistant to shocks. Thus, 1% increase of the deposits decreases the i^{th} firm's MES at time t

	MES				
Variables	**Coefficient**	**Standard Error**	**CI Lower**	**CI Upper**	**P-value**
Ln(Market Capitalization)	-0.058***	0.020	-0.097	-0.019	0.004
Ln(Debt)	0.006	0.013	-0.019	0.031	0.641
Ln(Deposits)	-0.169***	0.057	-0.280	-0.058	0.003
Ln(Insurance Reserves)	-0.085	0.063	-0.208	0.038	0.175
Return on Assets	0.003	0.005	-0.006	0.012	0.533
Dividend Yield	-0.018	0.012	-0.042	0.005	0.127
Price-to-Book-Value	$-3 \cdot 10^{-5}$	0.001	-0.003	0.003	0.831
Debt-to-Capital-Ratio	0.002	0.001	$-4 \cdot 10^{-5}$	0.004	0.108
Revenues	$-9.43 \cdot 10^{-9}$	$9.24 \cdot 10^{-9}$	$-2.75 \cdot 10^{-8}$	$-8.68 \cdot 10^{-9}$	0.307
Operating Expenses	$1.16 \cdot 10^{-8}$	10^{-8}	$-8.19 \cdot 10^{-9}$	$3.13 \cdot 10^{-8}$	0.252
Log return	0.012	0.050	-0.087	0.110	0.814
Volatility	50.686***	3.288	44.241	57.131	$< 2.2 \cdot 10^{-16}$
Skewness	-0.059***	0.016	-0.089	-0.028	$2 \cdot 10^{-4}$
Clustering Coefficient	3.863***	0.468	2.945	4.780	$< 2.2 \cdot 10^{-16}$
Betweenness Centrality	-1.418	1.958	-5.256	2.420	0.469

Notes: * p<0.1, ** p<0.05, *** p<0.01
Interactive Fixed Effect model: $Y_{it} = \delta_{it} D_{it} + X'_{it}\beta + \lambda'_i f_t + \sum_{k=1}^{T} \o_k \tau_k + \omega_i + \varepsilon_{it}$, only the β coefficients are reported. $D_{it} = 1$ if $i \in \mathcal{T}$ and $t > T_0$, 0 otherwise. δ_{it} is the heterogenous treatment effect, X_{it} vector of covariates with β coefficient vector, f_t denotes the factor(s) with λ_i loading vector. τ_k and ω_i denotes the time and individual fixed effects with $\o_k$ time coefficients. Only the β coefficients reported.

Table 2: Coefficient estimates of the Generalized Synthetic Control Method determining Marginal Expected Shortfall between 2016 and 2022

on average by 0.169%-points holding other variables constant. Deposits serve as a source of banks' liquidity, so the outcome matches the expectations: more liquidity reduces systemic risk. Similarly, larger firms have more capital, and their shock-absorbing capacity grows by size, but its impact on strengthening systemic stability is less than half compared to holding more deposits. The skewness of returns has almost the same effect as market capitalization. Nonetheless, the GSCM method did not find a significant relationship between the dividend policy, return on assets, and price-to-book value and systemic risk which were suggested as driving factors of (cumulative) abnormal returns by Adra et al. (2023), Wang et al. (2022) and Abbassi et al. (2022).

Table 3 compares possible variables to drive systemic risk suggested by the geopolitical risk- and (cumulative) abnormal returns-related literature. The table concludes that only size has the same impact on systemic risk as expected by the literature. Own capital should have the same impact as size since they are highly correlated due to regulation. Other variables were either not tested or insignificant. The possible explanation is that my research

Variable	Author(s)	Impact found in the literature	Relation to Systemic Risk
Book-to-Market	Abbassi et al. (2022)	Decrease CAR	Not impact MES
Return-on-Assets	Abbassi et al. (2022)	Decrease CAR	Not impact MES
Liquidity	Sun and Zhang (2022)	Increase CAR	Directly not tested
Cash	Lee and Wang (2021), Adra et al. (2023)	Decrease GPR	Not tested
Investments	Le and Tran (2021), Wang et al. (2019)	Increase GPR	Not tested
L/K	Wang et al. (2019)	Decrease GPR	Not tested
Dividends	Adra et al. (2023), Wang et al. (2019)	Increase GPR	Not impact MES
Share buybacks	Adra et al. (2023)	Increase GPR	Not tested
Credit growth	Demir and Danisman (2021)	Increase GPR	Not tested
Insurance premiums	Hemrit and Nakhli (2021)	Increase/Decrease GPR	Directly not tested
Size	Phan et al. (2022)	Decrease GPR	Decrease MES
Own Capital	Phan et al. (2022)	Decrease GPR	Directly not tested

Notes: CAR = cumulative abnormal returns, GPR = geopolitical risk, MES = Marginal Expected Shortfall, a measure of systemic risk. Instead of the Book-to-Market ratio, the Price-to-Book value was examined. The two indicators have an inverse relationship. *Directly not tested* means that the variable was not included in the model, but proxies for them were included. Liquidity correlates with bank deposits which reduce MES. Instead of insurance premiums, insurance reserves were tested. (Insurers, after cost deduction, reserve premiums immediately, so the two amounts are correlated. Reserves not affected by MES. Presumably, premiums would not impact systemic risk.) Own capital and market capitalization are strongly correlated due to regulation. Since market capitalization lowers systemic risk, own capital should also reduce MES.

Table 3: Comparison of variables determining systemic risk with factors applied in the abnormal return and geopolitical risk-related literature

includes return moments (i.e., volatility and skewness) and network measures (i.e., clustering coefficient and betweenness centrality), which affect systemic risk (only betweenness centrality is not). Consequently, I suggest future research revisit the role of factors concerning (cumulative) abnormal returns and geopolitical risk since they might be influenced by the omitted variables, namely the market structure and return moments.

Table 4 answers the central question of whether an invasion systemic risk premium exists for publicly traded financial companies with Russian subsidiaries at the outbreak of the war. To answer it, the average treatment effect on the treated ($\widehat{ATT}_t = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \left(Y_{it}(1) - \widehat{Y}_{it}(0)\right)$, for $t > T_0$.) is estimated. ATT was positive and significant at 5% significance level in 2022, when the Russia-Ukraine war escalated, meaning that the average, annualized invasion systemic risk premium is 16.7 basis points expressed in Marginal Expected Shortfall. In proportion, a company with a Russian subsidiary at the time of the invasion had - on average - by

		MES			
Year	**ATT (%)**	**Standard Error**	**CI Lower**	**CI Upper**	**P-value**
2016	0.082**	0.038	0.008	0.158	0.030
2017	-0.096***	0.031	-0.154	-0.031	0.002
2018	-0.011	0.042	-0.097	0.068	0.776
2019	0.066*	0.036	-0.003	0.136	0.060
2020	-0.013	0.044	-0.098	0.078	0.766
2021	-0.029	0.035	-0.100	0.039	0.448
2022	0.167**	0.087	0.004	0.335	0.046

Notes: Bootstrapped standard errors, sample size 1,000. * p<0.1, ** p<0.05, *** p<0.01
Average Treatment Effect on Treated: $\widehat{ATT}_t = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \left(Y_{it}(1) - \widehat{Y}_{it}(0)\right)$ for $t > T_0$, where $\widehat{Y}_{it}(0) = X'_{it}\widehat{\beta} + \widehat{\lambda}'_{it}\widehat{f}_t + \sum_{k=1}^{T} \widehat{\phi_k}\tau_k + \widehat{\omega_i},\ i \in \mathcal{T}, t > T_0$. $\widehat{\beta}$, $\widehat{\lambda}_{it}$, $\widehat{\phi_k}$ denotes the coefficient estimates. $\widehat{f}_t$ expresses the factors, τ_k and $\widehat{\omega_i}$ are the time and individual fixed-effects.

Table 4: Annual average Treatment Effect on Treated expressed in Marginal Expected Shortfall - *invasion systemic risk premium* - estimated by the Generalized Synthetic Control Method

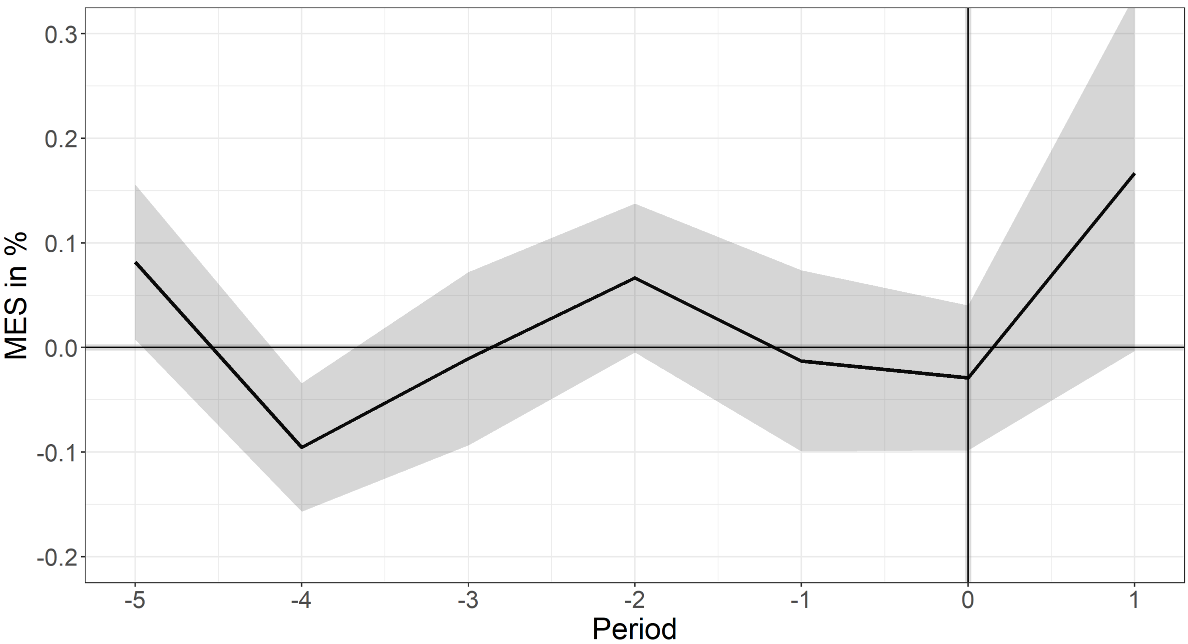


Figure 3: Average invasion systemic risk premium with 95% confidence intervals

9.3% larger MES in 2022 than its synthetic counterfactual holding other characteristics constant. In monetary terms, the invasion systemic risk premium means an average 96 million dollars additional loss for the treatment group.

Figure 3 presents the systemic risk premium of treated companies annually, where period 0 is 2021, and the year of interest is period 1 (2022). The visualization clearly shows the increase in systemic risk in the treatment group in 2022. The 95% grey-shaded confidence interval is broad, but it does not undermine the tendency that the systemic riskiness measured in MES grew in 2022. The average treatment effect on treated was significant not only in 2022 but in 2016, 2017, and 2019. However, ATT is more than twice as large in 2022 as in the highlighted pre-treatment years. To conclude, an invasion systemic risk premium exists - on average - 16.7 basis points for the treated financial companies in 2022.

6.3 Cross-sectional regressions

In the second part of the thesis, I examine only firms owning Russian subsidiaries at 24^{th} February 2022. Firstly, I investigated whether the corporate sanctions influenced the systemic risk of companies, including country and country group fixed effects. On the other hand, I run multinomial logistic regressions on the firm decisions to uncover which factors may have influenced the behavior of the companies.

I ran a linear regression on Marginal Expected Shortfall with equation (8). The model includes the following covariates: ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality. Company sanctions are compared to the base case of continuing operations in Russia. The reference group for country-fixed effects is the United States of America. Since country-fixed effects are included, I decided to cluster errors on the country level supported by the fact that international trade and oil and/or gas dependency from Russia significantly affected the (cumulative) abnormal returns, which are inhomogeneous across countries (Abbassi et al. 2022, Boubaker et al. 2022, Lo et al. 2022, Kumari et al. 2023, Sun and Zhang 2022).

$$\text{MES}_i = \text{Constant} + \beta \cdot \text{Covariates}_i + \phi \cdot \text{Sanction dummies}_i + \psi \cdot \text{Country dummies}_i + u_i \quad (8)$$

	MES		
Exit Completed	-0.005*	Germany	-0.005**
	(0.003)		(0.002)
Suspension	-0.001	India	-0.014***
	(0.002)		(0.002)
Withdrawal	-0.004	Italy	-0.010***
	(0.003)		(0.002)
Pausing Investments	-0.007	Japan	-0.018***
	(0.007)		(0.002)
Scaling Back	-0.004	Kazakhstan	-0.022***
	(0.003)		(0.005)
Australia	-0.013***	Netherlands	-0.008***
	(0.003)		(0.002)
Austria	-0.015***	Norway	$-4 \cdot 10^{-4}$
	(0.005)		(0.002)
Belgium	-0.015**	Poland	-0.009**
	(0.007)		(0.004)
Bulgaria	-0.015**	South Korea	-0.022***
	(0.006)		(0.003)
China	-0.020***	Spain	-0.012**
	(0.002)		(0.004)
Cyprus	-0.010***	Sweden	-0.003
	(0.003)		(0.003)
Denmark	-0.023***	Switzerland	-0.006***
	(0.004)		(0.001)
Finland	-0.006**	Turkey	-0.021***
	(0.002)		(0.002)
France	-0.008***	United Arab Emirates	-0.021***
	(0.002)		(0.005)
Georgia	-0.004	United Kingdom	-0.007***
	(0.004)		(0.001)
Other Covariates	YES		
Constant	0.013		
	(0.016)		
N	119		
R^2	0.848		

Notes: Country-level clustered errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
$\text{MES}_i = \text{Constant} + \beta \cdot \text{Covariates}_i + \phi \cdot \text{Sanction dummies}_i + \psi \cdot \text{Country dummies}_i + u_i$.
Other covariates are ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality.
Country dummies are compared to the *United States of America*.
The reference case for corporate reaction dummies is *continuing operations*.

Table 5: Corporate sanctions impact on systemic risk including country fixed effects in 2022

The results are presented in Table 5, confirming that leaving the country was the only decision in the one-year horizon that positively influenced the firm's systemic risk. MES of exited companies were, on average, by 0.005%-points smaller - ceteris paribus - compared to firms that maintained their operation. The systemic risk difference is relatively small, but this reaction was the only impactful decision significantly reducing Marginal Expected Shortfall. MES of an average firm exiting Russia decreased by 31.95%, holding all variables constant in 2022. In monetary terms, the exit saved, on average, about 107 million dollars for the leaving companies.

Table 5 shows that all country fixed effects are either significantly negative or zero. (Country fixed effects are compared to the United States.) Also, all firms headquartered outside the United States of America were safer (or equally secure) regarding systemic risk in 2022. The fixed effect values vary between -0.005 and -0.022. It means an average German firm saved 100 million dollars compared to a US-settled company. In addition, a standard Kazakh enterprise saved more than 440 million dollars. Sweden, Norway, and Georgia had an insignificant fixed effect. Also, they had the same risk as the United States. I did not find any common points between the three countries which might explain the same geopolitical risk as the United States had in 2022. Hence, Georgia is a Post-Soviet country that reacted cool to the invasion, Norway is a NATO member, but Sweden was a neutral country in 2022, but it declared its intention to join NATO in 2023.

The second regression equation is summarized in (9). Similarly, to regression (8), the outcome variable is Marginal Expected Shortfall, and the covariates are ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality. The only difference from (8) is that I added EU, NATO, and Anglo-Saxon country fixed effects instead of country dummies, plus interaction terms with ln(distance). The reason for the change was to examine the impact of geographical effects. The reference group of company decisions is continuing operations.

$$
\begin{aligned}
\mathrm{MES}_i = {} & \mathrm{Constant} + \beta \cdot \mathrm{Covariates}_i + \phi \cdot \mathrm{Sanction\ dummies}_i + \kappa_1 \cdot \mathrm{EU}_i \times \mathrm{Ln(Distance)}_i + \\
& \kappa_2 \cdot \mathrm{NATO}_i \times \mathrm{Ln(Distance)}_i + \kappa_3 \cdot \mathrm{Anglo\text{-}Saxon}_i \times \mathrm{Ln(Distance)}_i + \pi_1 \cdot \mathrm{EU}_i + \pi_2 \cdot \mathrm{NATO}_i + \\
& \pi_3 \cdot \mathrm{Anglo\text{-}Saxon}_i + \xi \cdot \mathrm{Ln(Distance)}_i + \upsilon_i
\end{aligned} \tag{9}
$$

	MES		
Exit Completed	-0.005*	Anglo-Saxon countries × Ln(Distance)	0.005
	(0.003)		(0.003)
Suspension	10^{-4}	NATO × Ln(Distance)	0.009***
	(0.002)		(0.002)
Withdrawal	-0.002	EU	-0.013
	(0.002)		(0.015)
Pausing Investments	-0.006	NATO	-0.030***
	(0.004)		(0.009)
Scaling Back	-0.003	Anglo-Saxon countries	-0.016
	(0.003)		(0.013)
EU × Ln(Distance)	0.004	Ln(Distance)	-0.008***
	(0.005)		(0.002)
Other Covariates	YES		
Constant	0.016		
	(0.010)		
N	119		
R^2	0.805		

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
$\text{MES}_i = \text{Constant} + \beta \cdot \text{Covariates}_i + \phi \cdot \text{Sanction dummies}_i + \kappa_1 \cdot \text{EU}_i \times \text{Ln(Distance)}_i + \kappa_2 \cdot \text{NATO}_i \times \text{Ln(Distance)}_i + \kappa_3 \cdot \text{Anglo-Saxon}_i \times \text{Ln(Distance)}_i + \pi_1 \cdot \text{EU}_i + \pi_2 \cdot \text{NATO}_i + \pi_3 \cdot \text{Anglo-Saxon}_i + \xi \cdot \text{Ln(Distance)}_i + \upsilon_i$.
Other covariates are ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality.
The reference case for corporate reaction dummies is *continuing operations.*

Table 6: Corporate sanctions impact on systemic risk including geographic integrations in 2022

The results are almost identical in Table 6 and in Table 5. The only significant decision was exiting the market (compared to remaining in Russia); the coefficient estimate is the same −0.005%-points. The coefficient of ln(distance) is negative, meaning that firms managed from closer countries to Ukraine are riskier, as Federle and Sehn (2022) highlighted. 1%-point increase in headquarter's distance from Ukraine reduces the predicted MES by 0.8 basis points holding everything else constant. NATO membership decreases the Marginal Expected Shortfall of the companies, in parallel with Boubaker et al. (2022), who also found that NATO membership signals security for investors. Nevertheless, the NATO and ln(distance) interaction is positive, meaning that NATO members far from Ukraine had a higher risk. This regression might explain why Kumari et al. (2023) associated NATO membership with higher loss in returns, while Boubaker et al. (2022) found the opposite effect. Namely, European NATO allies benefited from the North Atlantic Treaty Organization since their companies were less exposed to systemic risk, while firms settled in further NATO members had to bear a higher risk.

Finally, the relationship between firm characteristics and the management boards' decisions was tested. Multinomial logistic regression was estimated with the reference category of continuing operations in Russia ($j = 0$), described in (10).

$$P(\text{Sanction=j}) = \Lambda\left(\text{Constant}_j + \beta_j \cdot \text{Covariates}_i + \pi_{1j} \cdot \text{EU}_i + \pi_{2j} \cdot \text{NATO}_i + \pi_{3j} \cdot \text{Anglo-Saxon}_i + \xi_j \cdot \text{Ln(Distance)}\right), \tag{10}$$

where Λ is the logistic function and $j = 0,\ldots,J,$. Covariates are ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality. Ln(distance) interaction with EU, NATO, and Anglo-Saxon dummies is not included since the covariance matrix becomes singular. Marginal effects of the multinomial logistic regression at means are reported in Table 7. (For coefficient estimates please refer to Appendix E.) The marginal effects describe that insurance companies tended to exit Russia compared to continuing operations. 1% increase in insurance reserves of an average firm raises the leaving probability by 0.7 basis points rather than continuing operations. EU headquartered companies with average characteristics have 12.2%-points lower probability of exiting the Russian market, while in a NATO country settled average firm has 6.3%-points higher probability of leaving the market compared to continuing operations. The most influential driver of leaving the market is betweenness centrality. If it increases by $\frac{1}{1{,}000}$ leaving probability rises by 31%-points.

NATO and EU member banks with large deposit portfolios, high market capitalization, and substantial dividend yield tended to pause investments, assuming average corporate features compared to continuing operations. In NATO and EU resided headquarters of a standard company increases the probability of pausing investments by 52%-points and 15%-points rather than remaining on the Russian market. Nevertheless, companies leading operations from Anglo-Saxon countries are less likely to stop investments. An average firm with an Anglo-Saxon center decides to freeze investments by 36.2%-points less probably than continuing operations. Pausing investment decisions are taken by peripheral banks with low betweenness centrality and clustering coefficient.

Suspending operations is a more likely decision for non-leveraged, central firms. An aver-

	Corporate sanctions				
	Exit Completed	**Suspension**	**Withdrawal**	**Pausing Investments**	**Scaling Back**
Ln(Market Capitalization)	-0.028	0.072	-0.005	0.053**	-0.007
	(0.021)	(0.050)	(0.036)	(0.022)	(0.045)
Ln(Debt)	-0.011	-0.107**	0.038	-0.020	0.014
	(0.016)	(0.052)	(0.041)	(0.024)	(0.045)
Ln(Deposits)	0.003	0.007	-0.014**	0.005**	-0.005
	(0.004)	(0.007)	(0.006)	(0.003)	(0.006)
Ln(Insurance Reserves)	0.007*	0.001	0.002	0.005	-0.010
	(0.004)	(0.008)	(0.007)	(0.004)	(0.008)
Dividend Yield	-0.003	0.006	0.010	0.013**	0.011
	(0.009)	(0.016)	(0.017)	(0.006)	(0.011)
Price-to-Book-Value	$1.66 \cdot 10^{-4}$	$3.17 \cdot 10^{-4}$	$-2.31 \cdot 10^{-4}$	-0.003	0.003
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Revenues	$3.31 \cdot 10^{-9}$	$-1.64 \cdot 10^{-9}$	$-5.19 \cdot 10^{-9}$	$1.68 \cdot 10^{-9}$	$4.08 \cdot 10^{-9}$
	$(2.56 \cdot 10^{-9})$	$(5.44 \cdot 10^{-9})$	$(3.33 \cdot 10^{-9})$	$(3.40 \cdot 10^{-9})$	$(8.03 \cdot 10^{-9})$
Operating Expenses	$-4.15 \cdot 10^{-9}$	$4.17 \cdot 10^{-9}$	$2.53 \cdot 10^{-9}$	$-1.35 \cdot 10^{-9}$	$-6.18 \cdot 10^{-9}$
	$(2.88 \cdot 10^{-9})$	$(6.64 \cdot 10^{-9})$	$(4.43 \cdot 10^{-9})$	$(3.52 \cdot 10^{-9})$	$(8.34 \cdot 10^{-9})$
Total Debt-to-Capital	$3.46 \cdot 10^{-4}$	0.003	$-3.17 \cdot 10^{-5}$	$-4.04 \cdot 10^{-4}$	0.003
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Logreturn	0.047	0.210	0.092	-0.149	-0.316*
	(0.083)	(0.173)	(0.180)	(0.113)	(0.166)
Volatility	3.486	1.320	1.454	-2.217	-4.552
	(3.277)	(7.870)	(6.688)	(3.005)	(6.634)
Skewness	-0.004	-0.001	-0.011	0.037*	-0.006
	(0.022)	(0.048)	(0.035)	(0.020)	(0.051)
Betweenness Centrality	310.819**	1,000.772***	459.544***	-1,129.136**	-51.025
	(128.998)	(268.868)	(169.560)	(493.213)	(288.680)
Clustering Coefficient	1.156	-0.563	-0.297	-0.983***	1.678
	(1.211)	(1.472)	(1.181)	(0.324)	(1.152)
EU	-0.122**	-0.092	0.052	0.520***	-0.170**
	(0.059)	(0.080)	(0.043)	(0.037)	(0.067)
Anglo-Saxon countries	-0.061	0.039	0.418***	-0.362***	0.070
	(0.040)	(0.082)	(0.055)	(0.049)	(0.065)
NATO	0.063**	0.134	-0.023	0.150***	-0.275*
	(0.031)	(0.105)	(0.119)	(0.007)	(0.163)
Ln(Distance)	0.020	-0.181	-0.153*	0.908*	-0.297***
	(0.047)	(0.222)	(0.084)	(0.540)	(0.084)
N	119				

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Reference case for marginal effects is *continuing operations*. Multinomial logistic regression: $P(\text{Sanction=j}) = \Lambda\left(\text{Constant}_j + \beta_j \cdot \text{Covariates}_i + \pi_{1j} \cdot \text{EU}_i + \pi_{2j} \cdot \text{NATO}_i + \pi_{3j} \cdot \text{Anglo-Saxon}_i + \xi_j \cdot \text{Ln(Distance)}\right)$, $j = 0, 1, \ldots, J$, where Λ is the logistic function. Covariates are ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality.

$\partial P(\text{Sanction=j})/\partial X_k\big|_{X=\overline{X}} = P(\text{Sanction=j})\left(\beta_{jk} - \left[\sum_{h=1}^{J} \beta_{hk} exp(\beta_h X)\right] / \left[1 + \sum_{h=1}^{J} \beta_{hk} exp(\beta_h X)\right]\right)\Big|_{X=\overline{X}}$

Table 7: Multinomial logistic regression marginal effects at mean

age firm's 1% increase in debt reduces the probability of suspension by 10.7%-points. While $\frac{1}{10,000}$ increase of betweenness centrality for an average firm increases the probability of suspension by 10%-points compared to continuing operations.

The withdrawal is primarily chosen by average companies centrally located in the network and having headquarters in Anglo-Saxon countries rather than continuing operations. Anglo-Saxon centers increase the withdrawal probability by 41.8%-points, assuming average corporate characteristics. $\frac{1}{1,000}$ rise in the betweenness centrality accounts for 46%-points increase in the withdrawal probability for an average firm compared to continuing operations. Companies with higher returns and away from Ukraine rarely withdraw.

Scaling back activities are rarely decided by firms with EU and NATO settled headquarters, which are far from Ukraine and performed well in returns in 2022. Besides average characteristics, NATO- and EU-located firm centers reduce the probability of lowering activities by 27.5%-points and 17%-points compared to continuing operations. If the average firm has 1%-point higher return or distance from Ukraine, the probability of scaling back activities rises by ca. 30%-points rather than continuing operations.

To summarize, the regression results confirmed that only exiting the Russian market reduced significantly the systemic risk of financial companies. Firms having headquarters in the United States of America had, on average, higher systemic risk in 2022. Only Swedish, Norwegian, and Georgian companies had the same risk as the US ones. NATO membership - on average - reduces the Marginal Expected Shortfall of companies. My results refined Sun and Zhang (2022)'s analysis of sanctions. They concluded that stricter sanctions implied higher abnormal returns, while I found that exiting was the only impactful corporate sanction. Leaving the Russian market was the most likely decision of central insurance companies managed from a non-EU-but-NATO-member country rather than continuing operations.

7 Discussion

Possible limitations of the study are the strict assumptions of the Generalized Synthetic Control approach and the length of the pre-treatment period. Peri and Yasenov (2019) made a sensitivity analysis on the length of the pre-treatment period and concluded that the limited pre-treatment period might reduce the precision of the estimates short. The founders of the Synthetic Control method Abadie et al. (2010) and Abadie et al. (2015) used at least 20 periods before the treatment. As a possible limitation of the Generalized Synthetic Control Method, Yiqing (2017) emphasizes the short pre-treatment period and the assumption that the treatment and the control group have to have common support. When the pre-treatment period is small, it leads to a non-precise estimation of factor loadings. Since the dataset included only six years before the war, it might show an imprecise estimate of the coefficients. The GSCM identified no necessary factors in the model which might be related to the length of the pre-treatment period. Nevertheless, the reason is still being determined since the parallel trend assumption was tested successfully, so the model might not need time factors.

On the other hand, the invasion systemic risk premium was significant and positive but small. The analysis was replicated with ΔCoVaR to test the robustness of the results on the choice of systemic risk measure; the results are reported in Appendix F. The Average Treatment Effect on Treated was found insignificant in any general significance level, but the ATT showed the same tendency as visualized in Figure 4, only the confidence intervals became wider compared to Figure 3. Maybe, a more extended pre-treatment period could result in a more precise estimation and tighter confidence intervals. Or by creation, ΔCoVaR is resistant to the shift of the loss distribution (scale-invariance), which might result in a non-significant premium. The selection of state variables may influence the outcome. Nevertheless, the choice of the period depended on data availability, meaning that some companies were introduced to the stock market after 2016, and the many missing observation for a more extended pre-treatment period might cause some estimation hurdles. The data frequency was annual due to the balance sheet variables reporting frequency, which highly restricted the number of observations. Using balance sheet smoothing could result in a dataset with higher frequency (e.g., quarterly or monthly), extending the pre-treatment period.

The network variables were calculated using Billio et al. (2012)'s methodology, an early-stage framework for dealing with networks that might lead to inaccuracies in the network estimation. A more precise extension was proposed by (Reizinger 2020). The Granger-causality networks were estimated annually from approximately 260 observations. Nonetheless, a larger sample size would increase the detection of links, but the annual data frequency could not be held; also, there is a trade-off between the precision of network estimation and the size of the annual panel data; both cannot be resolved simultaneously. Binary treatment was applied, but the continuous treatment would reflect Russian exposure more precisely.

Unfortunately, the Russian subsidiaries are usually private firms, and their sales or market capitalization was unavailable, which could serve as possible weights for the treatment.

A further limitation of the paper is that it only focused on publicly traded companies, but many firms are not traded on the stock market, for instance, marine insurers, which were forced not to insure Russian oil and gas transport (Evenett and Pisani 2023) and their systemic risk might have been significantly affected by the sanctions. Naturally, the research can be extended in the future for private financial companies to get a more detailed overview of the Russian invasion of the financial industry.

8 Conclusion

I investigated the existence of *invasion systemic risk premium* using the data of publicly traded banks, insurance, and payment companies from 1^{st} January 2016 to 31^{st} December 2022. I compared the systemic risk of the firms owning Russian subsidiaries at the time of the Russian invasion of Ukraine (24^{th} February 2022) with their synthetic control group. I provided a comprehensive analysis of systemic risk changes induced by the Russia-Ukraine war reflecting on the development of balance sheet information of companies.

To match the observations, Yiqing (2017)'s Generalized Synthetic Control Method (GSCM) was applied, which is a more flexible framework compared to the Synthetic Control Method since it allows more than one treated unit, correlation of the treatment and the covariates, time-varying factors selected based on leave-one-out cross-validation, and standard errors and confidence intervals for causal inference that was produced via bootstrapping. GSCM was required due to auto-selection, and covariates were found to be highly imbalanced.

The analysis detected a significant *invasion systemic risk premium*. Treated companies had, on average, 16.7 basis points larger Marginal Expected Shortfall in 2022 than the synthetic control group firms. GSCM identified return volatility and clustering coefficient as the main drivers of systemic risk, while market capitalization, deposits, and skewness reduced the insolvency of financial firms. The result means, in monetary terms, a 96-million-dollar risk premium for publicly traded financial companies owning Russian subsidiaries. Nevertheless, the sensitivity test of the results using ΔCoVaR could not assure the results. The Average Treatment effect on Treated was found insignificant.

The second part of the study focused on the role of firm sanctions on Russia, investigated its impact on companies' systemic risk, and analyzed the influencing factors of the decisions. The causal analysis of corporate sanctions is a pioneer work in the literature; until now, only one descriptive summary was published reflecting on the sanctions (Evenett and Pisani 2023), and a regression analysis of returns (Sun and Zhang 2022). The regression analysis found that only the exit from the Russian market could significantly decrease the Marginal Expected Shortfall of publicly traded financial companies. Country fixed effects highlighted that the geographical location of headquarters influenced systemic risk. Namely, firms with headquarters in the USA were found riskier than others; only entities from Sweden, Norway, and Georgia had the same level of systemic risk as American ones. Headquarters in NATO member countries signaled higher security for the traders. On average, it reduced the firms' Marginal Expected Shortfall, but this result is more substantial for country headquarters close to the war zone: remote NATO members had a higher risk. Corporate sanctions were explained by multinomial logistic regression. Deeply integrated insurance companies directed from non-EU-but-NATO-member states were likelier to leave Russia than continue operations.

In conclusion, the study found a significant *invasion systemic risk premium* in the Marginal Expected Shortfall of publicly traded financial companies driven by return volatility and network structure. The market appreciated only the exit strategy as a significant reduction of systemic risk. Highly connected insurance companies managed from non-EU-but-NATO-member states left Russia with a higher probability rather than continuing operations. Systemic risk changes influence the financial system's stability due to the high integration. Therefore, monitoring the future development of systemic risk is essential for financial supervisory authorities, political actors, and, as confirmed, managers in the financial industry since managerial decisions can influence the systemic stability of companies.

Future research could examine the systemic risk spillovers from the financial industry to other sectors such as technology and energy markets, induced by the Russia-Ukraine war. Since technological and energy market investments are costly and the financial sector usually provides the funding, the risk transmission might occur faster than in other branches. The corporate sanctions of banks, payment, and insurance companies affect different sectors in the conflict zone since they could limit the operations of other firms by restricting financial resources and guarantees. Therefore, the risk propagation of corporate sanctions to non-financial industries might be a topic of future research.

Appendix

Appendix A and Appendix B are based on the work of Adrian and Brunnermeier (2011), but the formulation and notations were originally developed in the author's MSc thesis (Reizinger 2020, pp.94-96).

A ΔCoVaR

Adrian and Brunnermeier (2011) proposed a new systemic risk measure called conditional Value-at-Risk (CoVaR). The intuition of CoVaR is that bank i suffers a given loss with q probability induced by bank j. The given loss equals to the Value-at-Risk of firm i ($VaR_i(q)$).

$$Pr(r_j \leq CoVaR_{j|VaR_i(q),q}) = q \tag{11}$$

It is important to note that CoVaR is a pairwise and directed measure of loss. CoVaR is more general in that sense that $VaR_{i,q}$ can be replaced with different amounts of loss.

Nevertheless, an established critique against CoVaR is that it does not have a fix point which could help to determine whether a level of CoVaR indicates high or low systemic risk. I note that this is a fundamental problem of many systemic risk measures (like In, Out, InOut, or SRISK). Therefore Adrian and Brunnermeier (2011) proposed ΔCoVar which replaces the genral jth institution with the median firm's loss. Median firm can be interpreted as a proxy for the market. In this case Δ CoVaR measures the i^{th} company's marginal contribution to the system (Adrian and Brunnermeier 2011).

$$\Delta CoVaR_{j|i,q} = CoVaR_{j|X_i=VaR_i(q),q} - CoVaR_{j|X_i=Median_{i,q}} \tag{12}$$

B Estimation of ΔCoVaR

The estimation steps of ΔCoVaR are the following. Estimation steps follows Adrian and Brunnermeier (2011), Bernal et al. (2014) formulated by Reizinger (2020) (Adrian and Brunnermeier 2011, Bernal et al. 2014, p.14-15 and p.273-275).

1. Apply quantile regression to estimate the q^{th} tail of the i^{th} company return (13). T denotes the time index.

$$r_{i,t}(q) = \alpha_{i,q} + \gamma_{i,q} M_{t-1} + \epsilon_{i,t} \tag{13}$$

where $\alpha_{i,q}$ and $\gamma_{i,q}$ are constants, M_{t-1} expresses the lagged state variables, and $\epsilon_{i,t}$ denotes the error term. $\epsilon_{i,t}$ is an i.i.d. random variable, it has zero mean and unit variance.

2. Estimate the q^{th} Value-at-Risk of firm i at time t.

$$\widehat{Var_{i,t}}(q) = \hat{\alpha}_{i,q} + \hat{\gamma}_{i,q} M_{t-1}, \tag{14}$$

where $\hat{\alpha}_{i,q}$ and $\hat{\gamma}_{i,q}$ are the coefficient estimates from (13).

3. Estimate the q^{th} quantile of the system's return at time t:

$$r_{\text{system},t}(q) = \alpha_{\text{system}|i,q} + \beta_{\text{system}|i,q} \widehat{Var}_{i,t} + \gamma_{\text{system}|i,q} M_{t-1}. \tag{15}$$

The q^{th} quantile of the system's return is quantified with lagged state variables M_{t-1}), while $\alpha_{system|i,q}, \beta_{system|i,q}, \gamma_{system|i,q}$ are the coefficients, and $\epsilon_{i|system,t}$ expresses the innovation.

4. The estimated parameters in (15) are used to calculate the CoVaR of the system:

$$\widehat{CoVaR}_{system,t}(q) = \alpha_{system|i,q} + \beta_{system|i,q} r_{i,t} + \gamma_{system|i,q} M_{t-1} + \epsilon_{i|system,t}. \tag{16}$$

5. Finally, $\widehat{\Delta CoVaR}$ is computed.

$$\begin{aligned} \widehat{\Delta CoVaR}^{system|i,t}(q) = &\widehat{CoVaR}^{system|i,t}(q) - \widehat{CoVaR}_{system|i,t}(50\%) = \\ &\beta_{system|i,q}(\widehat{VaR}_{system|i,t}(q) - \widehat{VaR}_{system|i,t}(50\%)) \end{aligned} \tag{17}$$

Adrian and Brunnermeier (2011) used the following state variables for estimation (Adrian and Brunnermeier 2011, p.15-16):

- VIX index
- The difference of the three-month repo rate and the three-month bill rate called short term liquidity spread.
- The change in the three-month Treasury bill rate.
- The yield spread of the ten-year Treasury rate and the three-month bill rate.
- The difference of the BAA-rated bonds and the Treasury rate called credit spread.
- Weekly equity market return from CRSP.
- Weekly real estate sector return above the market return.

The mentioned factors were designed to the real estate market. To include the geopolitical risks in the model instead of the last two indices I added the daily change in GPR (Geopolitical Risk Index) introduced by Caldara and Iacoviell (2022) to the factors. Data values of GPR were accessed from https://www.matteoiacoviello.com/gpr.htm, the VIX index values originate from the Refinitiv Datastream, and bond yields are available on the website of the Federal Reserve. The data were downloaded on daily basis between 1^{st} January 2016 and 31^{st} December 2022. The changes in the GPR index were used as factors in the estimation of ΔCoVaR transformed by the formula $ln\left(\frac{X_t}{X_s}\right)\frac{1}{t-s}$, where t and s are consecutive trading days, but $t-s$ is not necessarily equal to one, e.g, due to the weekends or public holidays. Similar to MES, ΔCoVaR was estimated on a daily data and annual averages were used as outcome variables in the analysis.

C Generalized Synthetic Control Method

C.1 Assumptions

The formalisms, assumptions, and equations of the Generalized Synthetic Control method are discussed following Yiqing (2017) (Yiqing 2017, p.59-66).

Y_{it} denotes the outcome variable of unit i, and at time t, $\mathscr{T}$ denotes the treatment, and $\mathscr{C}$ denotes the control group. Observations in the treatment group are N_{tr}, while the number of units in the control group is N_{co}. Consequently, the total number of observations is $N = N_{tr} + N_{co}$. Data points are observed for T periods. T_0 denotes the number of pre-treatment periods of individual i, the treatment happens in (T_0+1) and $T-T_0$ equals to the number of post-treatment periods.

Assumption 1 (Functional form)

$$Y_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it}, \tag{18}$$

where D_{it} denotes the treatment dummy, namely:

$$D_{it} = \begin{cases} 1,\ if\ i \in \mathscr{T}\ and\ t > T_0, \\ 0\ otherwise. \end{cases} \tag{19}$$

δ_{it} represents the heterogenous treatment effect of unit i at time t. $X_{i,t}$ are the observed covariates, a $(k \times 1)$ vector. $\beta = [\beta_1, \ldots, \beta_k]'$ a $(k \times 1)$ vector. $f_t = [f_{1t}, \ldots, f_{rt}]$ denotes an $(r \times 1)$ vector of factors with $\lambda_i = [\lambda_{i1}, \ldots, \lambda_{ir}]$ $(r \times 1)$ loading vector. Finally, ε_{it} is a zero-mean innovation for unit i at time t.

To formalize the causality use the following notations: $Y_{it}(1)$ and $Y_{it}(0)$ are the outcome for the treated and the control group at time t for observation i.

$$Y_{it}(0) = x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it} \tag{20}$$

$$Y_{it}(1) = \delta_{it} + x'_{it}\beta + \lambda'_i f_t + \varepsilon_{it} \tag{21}$$

The treatment effect denoted by the difference of δ_{it} =(21) - (20) for any $i \in \mathcal{T}$ and $t > T_0$.

Assumption 1 can be reformulated as follows:

$$Y_i = D_i \circ \delta_i + X_i\beta + F\lambda_i + \varepsilon_i, i \in 1, 2, \ldots, N_{co}, N_{co}+1, \ldots, N, \tag{22}$$

where $Y_i = [Y_{i1}, Y_{i2}, \ldots, Y_{iT}]'$, $\delta_i = [\delta_{i1}, \delta_{i2}, \ldots, \delta_{iT}]'$, $\varepsilon_i = [\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{iT}]'$ are $(T \times 1)$ vectors. $X_i = [X_{i1}, X_{i2}, \ldots, X_{iT}]'$ is a $(T \times k)$, while $F_i = [F_{i1}, F_{i2}, \ldots, F_{iT}]'$ a $(T \times r)$ matrix.

$$Y_{co} = X_{co}\beta + F\Lambda'_{co} + \varepsilon_{co} \tag{23}$$

(23) denotes the functional form of the control group's equation with $Y_{co} = [Y_1, Y_2, \ldots, Y_{N_{co}}]$, $\varepsilon_{co} = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{N_{co}}]$ $(T \times N_{co})$ matrices. X_i has a dimension $T \times N_{co} \times p$, while $\Lambda_i = [\lambda_1, \lambda_2, \ldots, \lambda_{N_{co}}]$ is a $(N_{co} \times r)$ matrix. Further constraints for the factors are $FF'/T = I_r$ and $\Lambda'_{N_{co}}\Lambda_{N_{co}}$ is diagonal (Bai 2003, 2009).

The treatment effect on the treated can be expressed as:

$$ATT_{t,t>T_0} = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} [Y_{it}(1) - Y_{it}(0)] = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \delta_{it} \tag{24}$$

Assumption 2 (Strict exogeneity)

$$\varepsilon_{it} \perp D_{js}, x_{js}, \lambda_j, f_s, \forall i, j = 1, \dots N, \ and \ t, s = 1, \dots, T. \tag{25}$$

The strict exogeneity assumption means that the error term is independent of any unit's treatment, covariates, and cross-sectional and temporal factors at any time. The second assumption plays a role in causal identification and implies conditional mean independence: $\mathbb{E}\left(\varepsilon_{it}|D_{it}, x_{it}, \lambda_i, f_t\right) = \mathbb{E}\left(\varepsilon_{it}|x_{it}, \lambda_i, f_t\right)$. *Furthermore, assumption 2 allows the treatment and the covariates to be correlated, which usually happens in non-random experiments.*

Assumption 3 (Weak serial correlation) *Weak autocorrelation in the error term.*

Assumption 4 (Regularity conditions) *General regulatory conditions are met.*

The eighth moment of the error term is bounded, the fourth moment of $x_i t$ is bounded, and the covariance matrix of the factors and factor loadings of the control group are asymptotically positive definite (convergence in probability assumed).

Assumption 5 (Cross-sectional independent and homoscedastic error term.) *The error term is cross-sectionally independent and homoscedastic.*

C.2 Estimation

Step 1 To estimate the treatment effect on treated using a synthetic counterfactual $\widehat{\delta_{it}} = Y_{it}(1) - \widehat{Y_{it}}(0)$, firstly fit the IFE model on the control group's data.

$$\begin{gathered}\left(\widehat{\beta}, \widehat{F}, \widehat{\Lambda}_{co}\right) = \arg\min_{\widetilde{\beta}, \widetilde{F}, \widetilde{\Lambda}_{co}} \sum_{i \in \mathscr{C}} \left(Y_i - X_i\widetilde{\beta} - \widetilde{F}\widetilde{\lambda_i}\right)' \left(Y_i - X_i\widetilde{\beta} - \widetilde{F}\widetilde{\lambda_i}\right) \\ \text{s.t. } \widetilde{F}'\widetilde{F}/T = I_r \text{ and } \widetilde{\Lambda}'_{co}\widetilde{\Lambda}_{co} = \text{diagonal.}\end{gathered} \tag{26}$$

Step 2

$$\widehat{\lambda}_i = \arg\min_{\widetilde{\lambda}_i} \left(Y_i^0 - X_i^0\widehat{\beta} - \widehat{F}\widetilde{\lambda_i}\right)' \left(Y_i^0 - X_i^0\widehat{\beta} - \widehat{F}\widetilde{\lambda_i}\right) = \left(\widehat{F}^{0\prime}\widehat{F}^0\right)^{-1} \widehat{F}^{0\prime} \left(Y_i^0 - X_i^0\widehat{\beta}\right), i \in \mathscr{T}. \tag{27}$$

$\widehat{\beta}$ and $\widehat{F}^0$ come from the first step of estimation. "0" superscripts denote the pre-treatment periods.

Step 3

$$\widehat{Y}_{it}(0) = X'_{it}\widehat{\beta} + \widehat{\lambda}'_{it}\widehat{f}_t, i \in \mathcal{T}, t > T_0. \tag{28}$$

Now, the Average Treatment Effect on Treated can be computed.

$$\widehat{ATT}_t = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \left(Y_{it}(1) - \widehat{Y}_{it}(0) \right) \text{ for } t > T_0. \tag{29}$$

C.3 Factor selection

Factor selection is carried out via leave-one-out cross-validation.

Step 1 Start with r factors, estimate the IFE model as discussed in Appendix C.2 and obtain $\widehat{\beta}$ and $\widehat{F}$ using the control group's data.

Step 2 (a) Iterate over the pre-treatment periods. $s \in \{1, \ldots, T_0\}$. Run OLS regression to calculate the factor loading using the remaining pre-treatment periods (pre-treatment periods except for s).

$$\widehat{\lambda}_{i,-s} = \left(\widehat{F}^{0\prime}_{-s} \widehat{F}^{0}_{-s} \right)^{-1} \widehat{F}^{0\prime}_{-s} \left(Y^0_{i,-s} - X^0_{i,-s}\widehat{\beta} \right) \tag{30}$$

(b) Predict the treated outcome for period s. Estimate $\widehat{Y}_{is}(0) = x'_{is}\widehat{\beta} + \widehat{\lambda}'_{i,-s}\widehat{f}_s$ and save the errors, $e_{is} = Y_{is}(0) - \widehat{Y}_{is}(0), \forall i \in \mathcal{T}$.

Step 3 Calculate the mean square prediction error (MSPE) for r factors, MSPE(r) = $\sum_{s=1}^{T_0} \sum_{i \in \mathcal{T}} e^2_{is} / T_0$.

Step 4 Repeat the former steps (1 to 3) with a different number of factors (r) and compute the MSPEs.

Step 5 Select the number of factors (r^*) that minimizes MSPE.

C.4 Causal inference

A parametric bootstrap procedure is used to simulate treated counterfactuals and control units.

$$\begin{aligned} \widetilde{Y}_i(0) &= X_i\widehat{\beta} + \widehat{F}\widehat{\lambda}_i + \widetilde{\varepsilon}_i, \forall i \in \mathcal{C}, \\ \widetilde{Y}_i(0) &= X_i\widehat{\beta} + \widehat{F}\widehat{\lambda}_i + \widetilde{\varepsilon}^p_i, \end{aligned} \tag{31}$$

where $\widetilde{Y}_i(0)$ are simulated outcomes without treatment, $X_i\widehat{\beta} + \widehat{F}\widehat{\lambda}_i$ is the estimated conditional mean, and $\widetilde{\varepsilon}_i$ and $\widetilde{\varepsilon}_i^p$ are resampled prediction errors of individual i.

The algorithm steps for causal inference are the followings:

Step 1 Repeat a loop B_1 times.

(a) In step $m \in \{1,\ldots,B_1\}$ randomly select a control unit i if it is treated for $t > T_0$.

(b) Resample the control group excluding unit m with replacement of size N_{co}. Create a new sample with one "treated unit" and N_{co} resampled control units.

(c) Apply the estimation method (discussed in Appendix C.2) and compute the prediction errors: $\widehat{\varepsilon}^p_{(m)} = Y_i - \widehat{Y}_i(0)$. Finally, you will have a prediction error matrix $\widehat{e}^p = \{\widehat{\varepsilon}^p_{(1)},\ldots,\widehat{\varepsilon}^p_{(B_1)}\}$.

Step 2 Apply the Generalized Synthetic Control Method to the original data and estimate

(a) $\widehat{ATT}_t, \forall t > T_0$,

(b) $\widehat{\beta}, \widehat{F}, \widehat{\Lambda}_{co}$, and $\widehat{\lambda}_{j,j\in\mathcal{T}}$,

(c) $\widehat{Y}_{co} = \{\widehat{Y}_1(0), \widehat{Y}_2(0),\ldots,\widehat{Y}_{N_{co}}(0)\}$ and $\widehat{e} = \{\widehat{\varepsilon}_1,\widehat{\varepsilon}_2,\ldots,\widehat{\varepsilon}_{N_{co}}\}$.

Step 3 Run bootstrap B_2 times:

(a) In step $k \in \{1,2,\ldots,B_2\}$ create a bootstrap sample $S^{(k)}$:

$$\begin{aligned} \widetilde{Y}_i^{(k)}(0) &= \widehat{Y}_i(0) + \widetilde{\varepsilon}_i,\ i \in \mathscr{C}, \\ \widetilde{Y}_j^{(k)}(0) &= \widehat{Y}_j(0) + \widetilde{\varepsilon}_j^p,\ j \in \mathscr{T}, \end{aligned} \tag{32}$$

where $\widetilde{\varepsilon}_i$ and $\widetilde{\varepsilon}_i^p$ are selected from e and e^p and $\widehat{Y}_i(0) = X_i\widehat{\beta} + \widehat{F}\widehat{\lambda}_i$. The simulated treated counterfactuals do not contain the treatment effect.

(b) Now, use the Generalized Synthetic Control Method to sample $S^{(k)}$ and calculate the bootstrapped estimate $\widehat{ATT}_{t,t>T_0} = \{\widehat{ATT}^{(k)}_{t,t>T_0}\}$

Step 4 Compute the variance and the confidence interval of $\widehat{ATT}_{t,t>T_0}$ using the conventional percentile method (Efron 2004):

$$Var(\widehat{ATT}_{t,t>T_0}|D,X,\Lambda,F) = \frac{1}{B_2}\sum_{i=1}^{B_2}\left(\widehat{ATT}^{(i)}_{t,t>T_0} - \frac{1}{B_2}\sum_{j=1}^{B_2}\widehat{ATT}^{(j)}_{t,t>T_0}\right)^2 \tag{33}$$

D Pre-testing: parallel trends, auto-selection, covariate imbalance

The fundamental assumption of the Difference-in-Differences methodology is the parallel trend assumption tested using equation (34).

$$\begin{aligned}\text{Systemic risk}_{it} = &\sum_{t=-T}^{T_0+1} \beta_{1t}\text{Year}_t + \sum_{t=-T}^{T_0} \beta_{2t}\text{Year}_t \cdot \text{Treatment}_i + \beta_{2T_0+1}\text{Year}_{T_0+1} \cdot \text{Treatment}_i + \\ &\beta_3 X_{it} + \alpha_i + \varepsilon_{it},\end{aligned} \tag{34}$$

where the systemic risk measure is the Marginal Expected Shortfall of company i at time t, Year is the time dummy; treatment denotes companies with Russian subsidiary at the time of the invasion, X_{it} includes all balance sheet and network characteristics (geographical dummies and distance not, since they cannot be incorporated in the synthetic control method), α_i is the individual fixed effects, and ε_{it} is the error term. The parallel trend hypothesis is formulated in (35).

$$\mathbf{H_0} : \beta_{2t} = 0, \quad \forall t \leq T_0. \tag{35}$$

The p-value of the test equals 5.3%, meaning that the null hypothesis cannot be rejected at the general 5% significance level. Including geographical characteristics have the same result. Consequently, the parallel trend hypothesis is met.

	Treatment					
	No error clustering	EU-level error clustering	Anglo-Saxon--level error clustering	NATO-level error clustering	Country-level error clustering	Robust error clustering
Ln(Market Capitalization)	0.056	0.056	0.056	0.056	0.056	0.056
	(0.105)	(0.089)	(0.118)	(0.040)	(0.100)	(0.080)
Ln(Debt)	0.068	0.068	0.068	0.068	0.068	0.068
	(0.089)	(0.081)	(0.119)	(0.211)	(0.144)	(0.102)
Ln(Deposits)	-0.102***	-0.102	-0.102	-0.102	-0.102	-0.102
	(0.038)	(0.086)	(0.196)	(0.216)	(0.228)	(0.188)
Ln(Insurance Reserves)	-0.425***	-0.425***	-0.425	-0.425*	-0.425*	-0.425***
	(0.042)	(0.155)	(0.304)	(0.237)	(0.221)	(0.129)
Return on Assets	-0.042	-0.042**	-0.042	-0.042**	-0.042	-0.042
	(0.043)	(0.016)	(0.040)	(0.021)	(0.032)	(0.026)
Dividend Yield	-0.007	-0.007	-0.007	-0.007	-0.007	-0.007
	(0.091)	(0.029)	(0.020)	(0.040)	(0.059)	(0.051)
Price-to-Book-Value	$-3.79 \cdot 10^{-5}$	$-3.79 \cdot 10^{-5}$	$-3.79 \cdot 10^{-5}$	$-3.79 \cdot 10^{-5}$	$-3.79 \cdot 10^{-5}$	$-3.79 \cdot 10^{-5}$
	(0.014)	(0.004)	(0.007)	(0.005)	(0.004)	(0.004)
Revenues	$8.07 \cdot 10^{-8}$***	$8.07 \cdot 10^{-8}$**	$8.07 \cdot 10^{-8}$	$8.07 \cdot 10^{-8}$*	$8.07 \cdot 10^{-8}$*	$8.07 \cdot 10^{-8}$**
	$(9.83 \cdot 10^{-9})$	$(9.83 \cdot 10^{-9})$	$(9.83 \cdot 10^{-9})$	$(9.83 \cdot 10^{-9})$	$(9.83 \cdot 10^{-9})$	$(9.83 \cdot 10^{-9})$
Total Debt-to-Capital	0.004	0.004	0.004	0.004	0.004	0.004
	(0.011)	(0.034)	(0.009)	(0.006)	(0.017)	(0.018)
Log return	0.141	0.141	0.141	0.141*	0.141	0.141
	(0.631)	(0.174)	(0.156)	(0.076)	(0.165)	(0.117)
Volatility	-7.274	-7.274	-7.274	-7.274	-7.274	-7.274
	(21.923)	(18.736)	(11.780)	(10.949)	(19.584)	(11.140)
Skewness	-0.029	-0.029	-0.029***	-0.029	-0.029	-0.029
	(0.166)	(0.024)	(0.009)	(0.021)	(0.038)	(0.035)
Betweenness Centrality	0.191	0.191	0.191	0.191	0.191	0.191
	(26.549)	(6.334)	(4.532)	(3.003)	(4.855)	(2.845)
Clustering Coefficient	0.807	0.807	0.807	0.807	0.807	0.807
	(4.411)	(2.188)	(0.786)	(1.411)	(2.091)	(1.460)
Constant	-1.048	-1.048	-1.048	-1.048***	-1.048	-1.048
	(1.401)	(4.281)	(3.813)	(0.144)	(3.900)	(2.847)
N	1876					

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Treatment$_{it} = F(X'_{it}\theta + \eta_i) + \nu_{it}$, X_{it} denotes the dependent variables with θ coefficients, η_i individual effects, and ν_{it} is the error term. $F(\cdot)$ denotes the cumulative distribution function of the normal distribution. A random-effects model was estimated, since the fixed-effect model did not converge. Geographical dummies and ln(distance) were excluded hence the GSCM cannot handle dummies, and including distance resulted in a singular covariance matrix.

Table A.1: Auto-selection in the sample - Panel probit regression marginal effects at the mean with different error clustering

Difference	Control Group's Average	Treatment Group's Average	Year	Variable	N_{Co}	N_{Tr}	T-statistics	CI Lower	CI Upper	P-value	Significance
-0.623	15.429	16.053	2016	Ln(Market Capitalization)	151	119	-1.786	-1.312	0.066	0.076	*
-1.180	15.571	16.752	2017	Ln(Market Capitalization)	151	119	-5.473	-1.605	-0.756	$1.04 \cdot 10^{-7}$	***
-1.123	15.521	16.644	2018	Ln(Market Capitalization)	151	119	-5.222	-1.547	-0.700	$3.62 \cdot 10^{-7}$	***
-1.195	15.607	16.802	2019	Ln(Market Capitalization)	151	119	-5.405	-1.63	-0.759	$1.47 \cdot 10^{-7}$	***
-1.220	15.501	16.721	2020	Ln(Market Capitalization)	151	119	-5.564	-1.651	-0.788	$6.63 \cdot 10^{-8}$	***
-1.290	15.712	17.001	2021	Ln(Market Capitalization)	151	119	-5.936	-1.717	-0.862	$9.20 \cdot 10^{-9}$	***
-1.252	15.589	16.841	2022	Ln(Market Capitalization)	151	119	-5.728	-1.682	-0.822	$2.75 \cdot 10^{-8}$	***
-2.047	13.649	15.696	2016	Ln(Debt)	151	119	-3.762	-3.118	-0.976	0.000207	***
-2.335	13.706	16.040	2017	Ln(Debt)	151	119	-4.575	-3.339	-1.330	$7.34 \cdot 10^{-6}$	***
-2.350	13.802	16.152	2018	Ln(Debt)	151	119	-4.584	-3.36	-1.341	$7.04 \cdot 10^{-6}$	***
-2.415	13.883	16.298	2019	Ln(Debt)	151	119	-4.988	-3.368	-1.461	$1.12 \cdot 10^{-6}$	***
-2.117	14.259	16.376	2020	Ln(Debt)	151	119	-4.778	-2.989	-1.244	$2.93 \cdot 10^{-6}$	***
-2.168	14.538	16.706	2021	Ln(Debt)	151	119	-5.747	-2.911	-1.425	$2.64 \cdot 10^{-8}$	***
-2.178	14.515	16.692	2022	Ln(Debt)	151	119	-5.72	-2.928	-1.428	$3.10 \cdot 10^{-8}$	***
-3.624	4.711	8.336	2016	Ln(Deposits)	151	119	-3.316	-5.778	-1.471	0.001	***
-3.661	4.714	8.375	2017	Ln(Deposits)	151	119	-3.34	-5.821	-1.502	0.001	***
-3.613	4.738	8.351	2018	Ln(Deposits)	151	119	-3.274	-5.788	-1.439	0.001	***
-3.627	4.738	8.365	2019	Ln(Deposits)	151	119	-3.282	-5.804	-1.450	0.001	***
-3.644	4.760	8.404	2020	Ln(Deposits)	151	119	-3.282	-5.831	-1.456	0.001	***
-3.66	4.805	8.466	2021	Ln(Deposits)	151	119	-3.271	-5.865	-1.456	0.001	***
-3.641	4.818	8.459	2022	Ln(Deposits)	151	119	-3.253	-5.846	-1.436	0.001	***
5.789	8.930	3.140	2016	Ln(Insurance Reserves)	151	119	6.247	3.965	7.614	$1.65 \cdot 10^{-9}$	***
5.804	8.939	3.135	2017	Ln(Insurance Reserves)	151	119	6.261	3.979	7.629	$1.53 \cdot 10^{-9}$	***
5.783	8.935	3.152	2018	Ln(Insurance Reserves)	151	119	6.197	3.946	7.621	$2.18 \cdot 10^{-9}$	***
5.802	8.950	3.148	2019	Ln(Insurance Reserves)	151	119	6.216	3.964	7.640	$1.96 \cdot 10^{-9}$	***
5.835	8.986	3.151	2020	Ln(Insurance Reserves)	151	119	6.236	3.993	7.678	$1.75 \cdot 10^{-9}$	***
5.850	9.018	3.169	2021	Ln(Insurance Reserves)	151	119	6.223	3.999	7.700	$1.88 \cdot 10^{-9}$	***
6.023	9.021	2.998	2022	Ln(Insurance Reserves)	151	119	6.483	4.194	7.852	$4.32 \cdot 10^{-10}$	***
0.448	3.301	2.853	2016	Retrun on Assets	151	119	0.777	-0.687	1.583	0.438	
0.628	3.674	3.046	2017	Retrun on Assets	151	119	0.836	-0.852	2.107	0.404	
-0.109	3.269	3.378	2018	Retrun on Assets	151	119	-0.169	-1.377	1.159	0.866	
0.751	4.154	3.403	2019	Retrun on Assets	151	119	1.17	-0.513	2.016	0.243	
0.657	3.307	2.65	2020	Retrun on Assets	151	119	1.065	-0.558	1.872	0.288	
0.191	4.336	4.145	2021	Retrun on Assets	151	119	0.218	-1.54	1.923	0.828	
-0.264	2.852	3.116	2022	Retrun on Assets	151	119	-0.367	-1.681	1.153	0.714	

Note: * p<0.1, ** p<0.05, *** p<0.01

Table A.2: Comparison of covariates I.

Difference	Control Group's Average	Treatment Group's Average	Year	Variable	N_{Co}	N_{Tr}	T-statistics	CI Lower	CI Upper	P-value	Significance
-0.093	2.633	2.726	2016	Dividend Yield	151	119	-0.35	-0.615	0.429	0.727	
-0.165	2.429	2.594	2017	Dividend Yield	151	119	-0.66	-0.658	0.328	0.510	
-0.172	2.491	2.663	2018	Dividend Yield	151	119	-0.655	-0.687	0.344	0.513	
-0.387	2.726	3.113	2019	Dividend Yield	151	119	-1.37	-0.944	0.17	0.172	
0.876	4.111	3.235	2020	Dividend Yield	151	119	2.222	0.100	1.652	0.027	**
0.533	2.711	2.178	2021	Dividend Yield	151	119	2.158	0.047	1.019	0.032	**
-0.018	3.024	3.042	2022	Dividend Yield	151	119	-0.057	-0.632	0.596	0.955	
-0.537	1.642	2.178	2016	Price-to-Book-Value	151	119	-1.096	-1.503	0.43	0.275	
-1.061	0.923	1.984	2017	Price-to-Book-Value	151	119	-0.925	-3.32	1.198	0.356	
-1.164	1.808	2.972	2018	Price-to-Book-Value	151	119	-0.981	-3.511	1.183	0.328	
1.589	1.736	0.147	2019	Price-to-Book-Value	151	119	0.542	-4.220	7.399	0.589	
-1.947	1.247	3.193	2020	Price-to-Book-Value	151	119	-1.507	-4.505	0.611	0.134	
-0.101	1.606	1.707	2021	Price-to-Book-Value	151	119	-0.047	-4.391	4.189	0.963	
0.872	2.810	1.938	2022	Price-to-Book-Value	151	119	0.468	-2.798	4.542	0.640	
-13.937	37.405	51.343	2016	Debt-to-Capital-Ratio	151	119	-4.143	-20.563	-7.312	$4.69 \cdot 10^{-5}$	***
-14.947	37.582	52.529	2017	Debt-to-Capital-Ratio	151	119	-4.584	-21.368	-8.525	$7.15 \cdot 10^{-6}$	***
-14.871	38.321	53.191	2018	Debt-to-Capital-Ratio	151	119	-4.586	-21.256	-8.485	$7.08 \cdot 10^{-6}$	***
-15.342	37.792	53.134	2019	Debt-to-Capital-Ratio	151	119	-4.765	-21.682	-9.002	$3.15 \cdot 10^{-6}$	***
-15.844	38.396	54.240	2020	Debt-to-Capital-Ratio	151	119	-4.924	-22.180	-9.508	$1.51 \cdot 10^{-6}$	***
-15.664	38.054	53.718	2021	Debt-to-Capital-Ratio	151	119	-4.894	-21.967	-9.362	$1.73 \cdot 10^{-6}$	***
-17.025	38.080	55.106	2022	Debt-to-Capital-Ratio	151	119	-3.497	-26.619	-7.432	0.001	***
-18,508,870.99	11,182,471.50	29,691,342.50	2016	Revenues	151	119	-4.771	-26,175,358.33	-10,842,383.65	$4.40 \cdot 10^{-6}$	***
-18,655,575.46	11,428,638.95	30,084,214.42	2017	Revenues	151	119	-4.748	-26,421,384.52	-10,889,766.41	$4.90 \cdot 10^{-6}$	***
-19,100,674.91	12,423,428.63	31,524,103.54	2018	Revenues	151	119	-4.510	-27,472,885.75	-10,728,464.07	$1.34 \cdot 10^{-5}$	***
-20,288,281.26	13,230,440.82	33,518,722.08	2019	Revenues	151	119	-4.629	-28,951,869.63	-11,624,692.89	$8.17 \cdot 10^{-6}$	***
-18,537,689.59	12,430,529.23	30,968,218.82	2020	Revenues	151	119	-4.574	-26,547,256.82	-10,528,122.36	$1.02 \cdot 10^{-5}$	***
-19,719,236.75	14,122,654.62	33,841,891.37	2021	Revenues	151	119	-4.478	-28,421,214.71	-11,017,258.79	$1.50 \cdot 10^{-5}$	***
-18,553,689.86	14,039,072.38	32,592,762.24	2022	Revenues	151	119	-3.937	-27,869,271.4	-9,238,108.311	$1.29 \cdot 10^{-54}$	***
-15,607,610.2	9,685,101.662	25,292,711.87	2016	Operating Expenses	151	119	-4.567	-22,360,420.46	-8,854,799.946	$1.03 \cdot 10^{-5}$	***
-15,708,439.64	9,776,551.492	25,484,991.14	2017	Operating Expenses	151	119	-4.534	-22,555,632.47	-8,861,246.82	$1.20 \cdot 10^{-5}$	***
-15,998,741.67	10,605,886.75	26,604,628.41	2018	Operating Expenses	151	119	-4.367	-23,240,552.44	-8,756,930.896	$2.40 \cdot 10^{-5}$	***
-17,009,255.68	11,284,378.56	28,293,634.25	2019	Operating Expenses	151	119	-4.476	-24,520,520.22	-9,497,991.149	$1.53 \cdot 10^{-5}$	***
-15,647,942.76	10,733,126.38	26,381,069.13	2020	Operating Expenses	151	119	-4.453	-22,593,007.02	-8,702,878.496	$1.67 \cdot 10^{-5}$	***
-16,013,679.56	11,642,800.75	27,656,480.31	2021	Operating Expenses	151	119	-4.230	-23,494,928.11	-8,532,431.011	$4.08 \cdot 10^{-5}$	***
-15,280,906.05	12,019,974.11	27,300,880.16	2022	Operating Expenses	151	119	-3.718	-23,404,451.22	-7,157,360.892	$2.87 \cdot 10^{-4}$	***

Notes:Revenues and Operating Expenses are reported in thousand dollars, while Debt-to-Capital-Ratio in percentage. * p<0.1, ** p<0.05, *** p<0.01

Table A.3: Comparison of covariates II.

Difference	Control Group's Average	Treatment Group's Average	Year	Variable	N_{Co}	N_{Tr}	T-statistics	CI Lower	CI Upper	P-value	Significance
0.047	0.066	0.019	2016	Return	151	119	1.753	-0.006	0.099	0.0807	*
-0.057	0.169	0.226	2017	Return	151	119	-1.972	-0.113	$-8.33 \cdot 10^{-5}$	0.0497	**
0.045	-0.076	-0.121	2018	Return	151	119	1.010	-0.043	0.132	0.314	
-0.071	0.079	0.150	2019	Return	151	119	-1.658	-0.156	0.013	0.099	*
-0.047	-0.024	0.023	2020	Return	151	119	-1.187	-0.125	0.031	0.236	
-0.116	0.073	0.189	2021	Return	151	119	-2.039	-0.228	-0.004	0.043	**
0.030	-0.089	-0.119	2022	Return	151	119	0.753	-0.048	0.108	0.452	
-0.001	0.017	0.018	2016	Volatility	151	119	-0.893	-0.003	0.001	0.373	
0.001	0.013	0.012	2017	Volatility	151	119	1.526	$-3.24 \cdot 10^{-4}$	0.003	0.128	
0.002	0.016	0.015	2018	Volatility	151	119	1.691	$-2.56 \cdot 10^{-4}$	0.003	0.092	*
$-4.59 \cdot 10^{-4}$	0.015	0.015	2019	Volatility	151	119	-0.465	-0.002	0.001	0.642	
0.002	0.029	0.027	2020	Volatility	151	119	1.465	-0.001	0.004	0.144	
0.001	0.017	0.016	2021	Volatility	151	119	1.282	-0.001	0.003	0.201	
-0.001	0.021	0.022	2022	Volatility	151	119	-0.962	-0.003	0.001	0.337	
0.338	-0.261	-0.600	2016	Skewness	151	119	2.304	0.049	0.628	0.022	**
-0.397	-0.092	0.305	2017	Skewness	151	119	-2.537	-0.705	-0.089	0.012	**
0.145	-0.214	-0.36	2018	Skewness	151	119	1.079	-0.12	0.410	0.281	
-0.190	-0.220	-0.030	2019	Skewness	151	119	-1.471	-0.445	0.064	0.143	
-0.089	-0.182	-0.093	2020	Skewness	151	119	-0.763	-0.318	0.140	0.446	
0.180	0.162	-0.019	2021	Skewness	151	119	1.497	-0.057	0.418	0.136	
-0.227	-0.288	-0.061	2022	Skewness	151	119	-2.002	-0.451	-0.004	0.046	**
-0.004	0.010	0.014	2016	Clustering Coefficient	151	119	-0.82	-0.014	0.006	0.414	
0.001	0.001	0	2017	Clustering Coefficient	151	119	1.399	-0.001	0.003	0.164	
-0.007	0.020	0.027	2018	Clustering Coefficient	151	119	-1.388	-0.016	0.003	0.166	
0.004	0.012	0.008	2019	Clustering Coefficient	151	119	0.985	-0.004	0.013	0.326	
0.006	0.077	0.071	2020	Clustering Coefficient	151	119	0.814	-0.009	0.022	0.416	
0.004	0.010	0.005	2021	Clustering Coefficient	151	119	1.806	$-4.01 \cdot 10^{-4}$	0.009	0.072	*
-0.005	0.023	0.028	2022	Clustering Coefficient	151	119	-1.066	-0.014	0.004	0.288	
$2.95 \cdot 10^{-4}$	$7.11 \cdot 10^{-3}$	$4.16 \cdot 10^{-4}$	2016	Betweenness Centrality	151	119	0.939	$-3.24 \cdot 10^{-4}$	0.001	0.349	
$-1.12 \cdot 10^{-5}$	$9.96 \cdot 10^{-6}$	$2.11 \cdot 10^{-4}$	2017	Betweenness Centrality	151	119	-0.900	$-3.57 \cdot 10^{-5}$	$1.34 \cdot 10^{-5}$	0.370	
$2.31 \cdot 10^{-4}$	$9.55 \cdot 10^{-4}$	$7.24 \cdot 10^{-4}$	2018	Betweenness Centrality	151	119	0.498	$-6.84 \cdot 10^{-5}$	$1.15 \cdot 10^{-5}$	0.619	
$-4.93 \cdot 10^{-5}$	$7.98 \cdot 10^{-7}$	$5.72 \cdot 10^{-5}$	2019	Betweenness Centrality	151	119	-1.604	$-1.11 \cdot 10^{-4}$	$1.16 \cdot 10^{-5}$	0.111	
-0.001	0.006	0.007	2020	Betweenness Centrality	151	119	-0.462	-0.008	0.005	0.645	
$-4.50 \cdot 10^{-6}$	$3.82 \cdot 10^{-5}$	$4.27 \cdot 10^{-4}$	2021	Betweenness Centrality	151	119	-0.181	$5.34 \cdot 10^{-5}$	$4.44 \cdot 10^{-5}$	0.857	
$-3.20 \cdot 10^{-5}$	$3.75 \cdot 10^{-4}$	$6.95 \cdot 10^{-5}$	2022	Betweenness Centrality	151	119	-1.267	$-8.19 \cdot 10^{-5}$	$1.79 \cdot 10^{-5}$	0.207	

Note: * p<0.1, ** p<0.05, *** p<0.01

Table A.4: Comparison of covariates III.

E Cross-sectional regression results

	Corporate Sanctions				
	Exit Completed	Suspension	Withdrawal	Pausing Investments	Scaling Back
Ln(Market Capitalization)	-0.099	0.830*	0.469	2.733	0.339
	(0.562)	(0.495)	(0.469)	(1.863)	(0.487)
Ln(Debt)	-0.684	-1.007*	-0.267	-1.307	-0.321
	(0.523)	(0.560)	(0.564)	(1.468)	(0.541)
Ln(Deposits)	0.024	0.002	-0.136*	0.221	-0.067
	(0.097)	(0.067)	(0.082)	(0.217)	(0.074)
Ln(Insurance Reserves)	0.155	0.036	0.043	0.261	-0.044
	(0.098)	(0.069)	(0.081)	(0.249)	(0.093)
Return on Assetst	-0.021	-0.098	-0.067	0.094	-0.094
	(0.100)	(0.085)	(0.078)	(0.111)	(0.093)
Dividend Yield	0.126	0.242	0.291	0.730	0.260**
	(0.205)	(0.153)	(0.199)	(0.506)	(0.121)
Price-to-Book-Value	0.011	0.007	0.007	-0.112	0.030
	(0.022)	(0.017)	(0.012)	(0.113)	(0.020)
Revenues	$7.20 \cdot 10^{-8}$	$-3.93 \cdot 10^{-9}$	$-3.44 \cdot 10^{-8}$	$7.84 \cdot 10^{-8}$	$3.46 \cdot 10^{-8}$
	$(5.95 \cdot 10^{-8})$	$(4.43 \cdot 10^{-8})$	$(4.10 \cdot 10^{-8})$	$(1.72 \cdot 10^{-7})$	$(7.79 \cdot 10^{-8})$
Operating Expenses	$-1.04 \cdot 10^{-7}$	$-1.03 \cdot 10^{-9}$	$-2.40 \cdot 10^{-9}$	$-7.40 \cdot 10^{-8}$	$-6.58 \cdot 10^{-8}$
	$(6.66 \cdot 10^{-8})$	$(5.11 \cdot 10^{-8})$	$(5.09 \cdot 10^{-8})$	$(1.72 \cdot 10^{-7})$	$(8.34 \cdot 10^{-8})$
Total Debt-to-Capital	0.042	0.049**	0.040	0.010	0.056**
	(0.026)	(0.024)	(0.024)	(0.050)	(0.028)
Log return	0.568	0.775	0.473	-6.652	-2.507*
	(1.689)	(1.274)	(1.868)	(6.928)	(1.462)
Volatility	68.587	9.360	12.948	-94.920	-29.576
	(62.443)	(57.871)	(67.169)	(172.177)	(58.327)
Skewness	-0.055	0.040	-0.061	1.646	-0.026
	(0.530)	(0.472)	(0.536)	(1.051)	(0.570)
Betweenness Centrality	11,100.315***	10,037.844***	9,836.262***	-45,387.474	4,733.915
	(3,234.228)	(3,216.251)	(3,250.059)	(30,729.796)	(3,785.653)
Clustering Coefficient	28.619	2.654	4.199	-39.211	18.100
	(24.358)	(14.448)	(14.957)	(24.948)	(13.678)
EU	-1.856	1.181	17.842***	42.079	-0.709
	(1.311)	(2.136)	(2.220)	(47.775)	(1.278)
Anglo-Saxon countries	-3.388	1.980	20.595***	-17.473***	2.628*
	(2.078)	(1.986)	(2.332)	(3.963)	(1.534)
NATO	2.048	0.855	-0.526	21.290***	-1.828
	(1.484)	(1.679)	(1.593)	(6.751)	(1.496)
Ln(Distance)	0.877	0.022	-0.965	40.425	-1.817**
	(0.837)	(0.875)	(0.840)	(34.758)	(0.853)
Constant	2.733	-2.641	-20.032**	-223.895	4.049
	(6.473)	(6.022)	(7.888)	(176.909)	(5.393)
Psuedo R^2	0.328				
N	119				

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Reference case for marginal effects is *continuing operations*. Multinomial logistic regression:
$P(\text{Sanction=j}) = \Lambda\left(\text{Constant}_j + \beta_j \cdot \text{Covariates}_i + \pi_{1j} \cdot \text{EU}_i + \pi_{2j} \cdot \text{NATO}_i + \pi_{3j} \cdot \text{Anglo-Saxon}_i + \xi_j \cdot \text{Ln(Distance)}\right)$, $j = 0, 1, \ldots, J$, where Λ is the logistic function. Covariates are ln(market capitalization), ln(debt), ln(deposits), ln(insurance reserves), return on assets, dividend yield, price-to-book-value, debt-to-capital-ratio, revenues, operating expenses, return, volatility, skewness, clustering coefficient, and betweenness centrality.

Table A.5: Multinomial logistic regression coefficient estimates

F Robustness test

Variables	Coefficient	Standard Error	CI Lower	CI Upper	P-value
Ln(Market Capitalization)	−0.009	0.008	−0.025	0.008	0.286
Ln(Debt)	0.008	0.006	−0.004	0.020	0.202
Ln(Deposits)	−0.048	0.027	−0.101	0.005	0.077
Ln(Insurance Reserves)	−0.010	0.032	−0.072	0.053	0.765
Return on Assets	0.0003	0.002	−0.004	0.005	0.887
Dividend Yield	−0.008	0.006	−0.020	0.005	0.222
Price-to-Book-Value	−0.0002	0.001	−0.001	0.001	0.734
Debt-to-Capital-Ratio	0.001	0.001	−0.001	0.002	0.440
Revenues	0	0	−0	0	0.953
Operating Expenses	0	0	−0	0	0.767
Return	−0.056	0.023	−0.101	−0.011	0.014
Volatility	1.435	1.550	−1.602	4.473	0.354
Skewness	−0.020	0.007	−0.034	−0.006	0.005
Clustering Coefficient	2.663	0.247	2.178	3.148	0
Betweenness Centrality	−0.392	1.198	−2.740	1.955	0.743

Note: * p<0.1, ** p<0.05, *** p<0.01

Interactive Fixed Effect model: $Y_{it} = \delta_{it} D_{it} + X'_{it}\beta + \lambda'_i f_t + \sum_{k=1}^{T} \o_k \tau_k + \omega_i + \varepsilon_{it}$, only the β coefficients are reported. $D_{it} = 1$ if $i \in \mathcal{T}$ and $t > T_0$, 0 otherwise. δ_{it} is the heterogenous treatment effect, X_{it} vector of covariates with β coefficient vector, f_t denotes the factor(s) with λ_i loading vector. τ_k and ω_i denotes the time and individual fixed effects with $\o_k$ time coefficients. Only the β coefficients reported.

Table A.6: Coefficient estimates of the Generalized Synthetic Control Method determining ΔCoVaR between 2016 and 2022

			ΔCoVaR		
Year	**ATT (%)**	**Standard Error**	**CI Lower**	**CI Upper**	**P-value**
2016	−0.001	0.013	−0.025	0.027	0.932
2017	−0.011	0.016	−0.042	0.019	0.462
2018	0.005	0.017	−0.029	0.038	0.768
2019	−0.006	0.015	−0.035	0.024	0.706
2020	0.024	0.028	−0.030	0.077	0.396
2021	−0.011	0.014	−0.036	0.018	0.428
2022	0.038	0.054	−0.067	0.142	0.466

Note: * p<0.1, ** p<0.05, *** p<0.01
Average Treatment Effect on Treated: $\widehat{ATT}_t = \frac{1}{N_{tr}} \sum_{i \in \mathcal{T}} \left(Y_{it}(1) - \widehat{Y}_{it}(0)\right)$ for $t > T_0$, where $\widehat{Y}_{it}(0) = X'_{it}\widehat{\beta} + \widehat{\lambda}'_{it}\widehat{f}_t + \sum_{k=1}^{T} \widehat{\varpi_k}\tau_k + \widehat{\omega_i}$, $i \in \mathcal{T}$, $t > T_0$. $\widehat{\beta}$, $\widehat{\lambda}_{it}$, $\widehat{\varpi_k}$ denotes the coefficient estimates. $\widehat{f}_t$ expresses the factors, τ_k and $\widehat{\omega_i}$ are the time and individual fixed-effects.

Table A.7: Annual average Treatment Effect on Treated expressed in ΔCoVaR - *invasion systemic risk premium* - estimated by the Generalized Synthetic Control Method

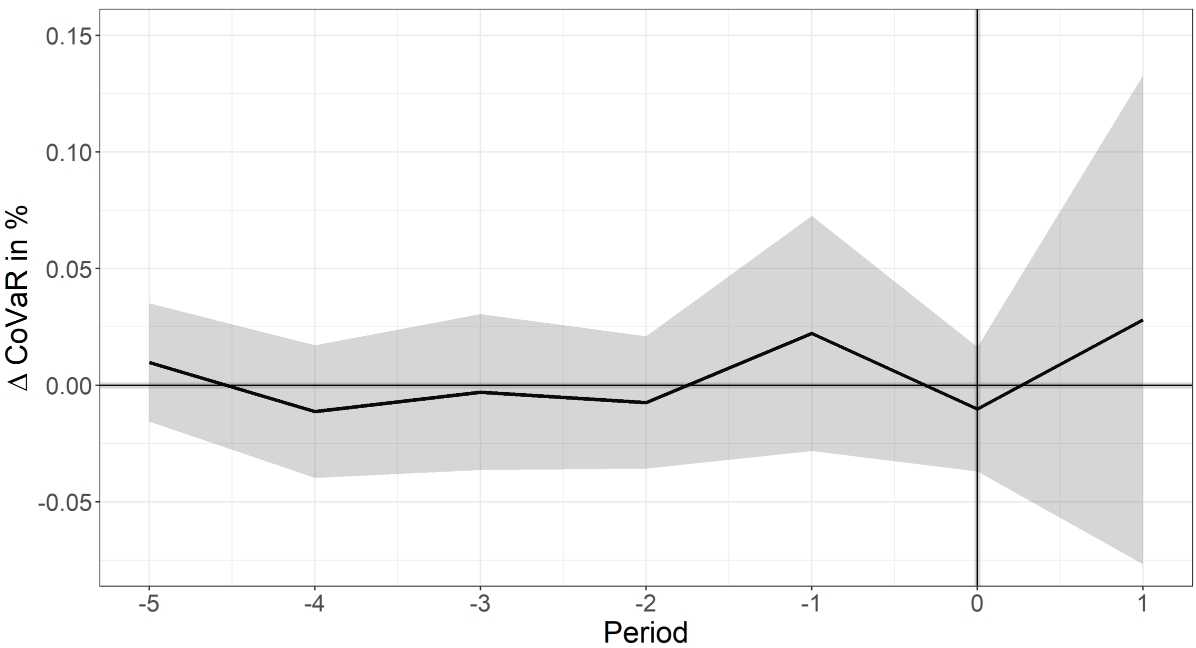


Figure A.1: Average invasion systemic risk premium with 95% confidence intervals (ΔCoVaR)

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