The price of geoeconomic dependence: Sanction intensity and corporate credit spreads

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Abstract

This paper studies the corporate implications of sanction intensity using the example of the EU-Russia conflict after Russia's war on Ukraine. Exploiting changes in the variance-covariance structure of financial and news variables with gas prices on official sanction and countersanction announcement days, the paper presents a new approach to the identification of sanction intensity shocks. Sanction intensity raises credit spreads, as both firm default risk and risk premia rise, with stronger effects for firms, industries, and countries highly dependent on Russia before the war. The sanction intensity shock differs from standard geopolitical and gas supply shocks in particular in its effect on corporate default risk. The financial cost of sanction intensity spills over to the real economy as corporate investment declines, primarily due to higher borrowing costs, while bankruptcies rise.

Keywords: Geoeconomics, Sanctions, Corporate Credit Market, Default Risk, Geopolitical Shocks

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1. Introduction

Geopolitical conflict and geoeconomic power struggles are once again on the rise. The growing use of international sanctions shows that countries are increasingly leveraging economic and financial dependencies for geopolitical purposes (Felbermayr et al., 2020). While sanctions have become a powerful economic weapon in a globalized world, they typically come at a cost. This cost is determined by the relative strength of dependencies between the conflict parties. A striking example of the use of geoeconomic power is the EU-Russia conflict over Ukraine. Russia's full-scale attack on Ukraine in February 2022 posed a substantial challenge for policymakers in Europe. While Russia relied on western technology imports, European reliance on Russian gas, accounting for more than 40% of all gas supplies before the war, was Russia's strongest geoeconomic lever and an existential threat to many firms in Europe. Several factors further exacerbated European reliance on Russian energy supplies: The physical infrastructure in the form of gas pipelines and oil refineries was specifically designed to facilitate supply from Russia and few alternatives existed. Russia had further ensured to maximize European reliance on energy imports by depleting European gas reserves in the buildup to the invasion. Policymakers in Europe were aware that far-reaching sanctions on Russia could lead to a complete disruption of gas supplies with potentially severe consequences for domestic energy-intensive industries. More generally, the costs of sanctions crucially depend on the target country's ability to respond and the relative balance of geoeconomic power. The higher the reliance on inputs into production (e.g. the higher the import share and the lower the substitutability due to either monopoly power or technological lock-in), the higher the geoeconomic power, and the stronger the price response in the importing country. Gas prices in Europe more than tripled as a response to the conflict, highlighting Europe's strong dependence. The case of Europe's dependence on Russian energy is an illustrative example of the use of geopolitical pressure (Clayton et al., 2025) in the context of a military conflict.

This paper provides a novel framework for measuring sanction intensity using event-day heteroskedasticity following Rigobon (2003), Rigobon and Sack (2004), Wright (2012), and Boer et al. (2023), where event days correspond to announcement days of sanction and countersanction measures by the EU and Russia between 2014 and 2024. The degree of co-movement between financial variables, geopolitical news, and gas prices determines the daily sanction intensity. The approach is data-driven in that the shock can pick up non-specified days of elevated sanction intensity, and its applicability can be confirmed by formal statistical tests. The results show that Europe's economic reliance on Russia had severe consequences for core industries once sanctions and countersanctions were imposed. The paper identifies EU-Russia sanction shocks and quantifies the cost for firm financing on euro area credit markets [1]. Sanction shocks capture both the intensity of newly announced sanctions, as well as the perceived risk of Russian counter-measures as reflected in financial and gas markets. In particular, the covariance of financial and geopolitical news variables with gas prices strengthens substantially on announcement days. The strength of EU-Russia sanction intensity observed at the start of the full-scale invasion is associated with an increase in credit spreads of 16 basis points. This effect is around 30% stronger for firms that were highly reliant on Russia before the full-scale invasion. The increase in spreads is not only driven by higher risk aversion as reflected in higher excess bond premia, but also in elevated levels of corporate default risk. After 100 days, half of the increase in credit spreads can be attributed to increased fundamental corporate default risk. In this dimension the sanction intensity shock differs substantially from other shocks such as monetary policy-, uncertainty-, gas price-, or geopolitical risk shocks, which primarily affect the excess bond premium component of the spread. The financial response to sanction intensity further translates into real economic costs by reducing firm investment and increasing corporate bankruptcies.

So far, the firm-level cost of sanctions and geoeconomic disintegration have not been well understood. This paper addresses this gap, focusing on a period of rapid economic disintegration in a setting of pronounced economic dependence. To the best of my knowledge, this is the first paper to empirically estimate sanction intensity shocks and to document the corporate cost of a rapid unwinding of geoeconomic dependence due to conflict. More recently, China's export restrictions on rare earths and the US decision to restrict the export of advanced semiconductors to China highlight that economic dependencies are increasingly weaponized to pursue geopolitical goals. The EU-Russia economic conflict after Russia's full-scale invasion of Ukraine can thus be seen as a first manifestation of geoeconomic power struggles in such a new environment.

Related Literature

Felbermayr et al. (2020) define sanctions as "restrictive measures applied by individual nations, country groups, the United Nations (UN), and other international organizations, to address different types of violations of international norms by inducing target countries to change their behaviour or to constrain their actions." In line with this definition, sanction events will be defined as official announcements of restrictive measures by the EU in response to the Russian invasion of Ukraine, but

[1] Around 20% of total non-financial corporations' (NFC) financing in the euro area was channeled through the credit market by the end of 2022: ECB FSR, May 2023

will also include the Russian countermeasures. In the context of geopolitical power struggles, the cost of sanctions for domestic firms is crucially determined by the relative geoeconomic power of the sanctioning and the sanctioned country. Russia responded to EU sanctions by imposing countersanctions in the form of presidential decrees and by cutting gas supplies to sanctioning countries. Several papers have already investigated the global financial and macroeconomic effects of the Russian war against Ukraine (Gopinath et al., 2024; Caldara et al., 2022; Korovkin and Makarin, 2023; Corsetti et al., 2024; Crozet and Hinz, 2020). Theoretical papers by Bachmann et al. (2024) and Ghironi et al. (2024) provide a useful quantitative benchmark to approximate the economic cost of EU-Russia sanctions in a counterfactual analysis. Few papers have, however, empirically analyzed the implications of the conflict for firms, and no paper has studied the role of sanctions in this context. Federle et al. (2022) document in an event-study setting, around the invasion of Ukraine in February 2022, a proximity penalty on stock markets. This paper provides an approach to systematically measure sanction intensity in the context of the EU-Russia conflict and studies the corporate implications of sanctions, focusing on firms' geoeconomic dependence on Russia, rather than on geographic proximity.

The paper also contributes to the fast-growing literature on geoeconomic power and sanctions (Itskhoki and Mukhin, 2025; Clayton et al., 2024; Clayton et al., 2023; Bianchi and Sosa-Padilla, 2024; Becko, 2024). Focusing on firms, operating in an environment of sanctions and power struggles, this paper provides a new perspective on the effects of sanction intensity on the economy. This paper also relates to the literature developing new approaches to estimating geopolitical fragmentation and risk and its economic spillovers (Caldara and Iacoviello, 2022; Bondarenko et al., 2024; Fernández-Villaverde et al.; 2024) and to papers studying the importance of supply chains for the transmission of conflict and war across firms and borders (Glick and Taylor, 2010; Couttenier et al., 2022; Federle et al., 2024). While previous papers have used identification based on event-day heteroskedasticity to study war and geopolitical risk (Rigobon and Sack, 2005; Aizenman et al., 2024), this is the first paper to estimate and study sanction intensity shocks specifically.

The remaining paper is structured in seven additional sections. Section 2 describes the relevant data and Section 3 provides evidence for elevated sanction intensity on official announcement days. The methodology used to identify the sanction intensity shock is then outlined in Section 4 and results for credit spreads and default risk are presented in Section 5. The firm-specific impact of sanction intensity is studied in Section 6 and the impact on aggregate realized default risk is discussed in Section 7. Section 8 concludes.

2. Data

2.1. Construction, decomposition, and aggregation of credit spreads

To calculate credit spreads, data on bond yields for outstanding corporate bonds, their remaining duration, and a maturity-matched measure for the risk-free rate are collected. Corporate bond yields and the remaining bond duration are retrieved from Datastream. In line with the literature, all outstanding euro-denominated senior-unsecured bonds issued by NFCs from Datastream for which yield data is available are included. The sample of debt securities is further restricted to bonds with a face value above 1 million euro that are traded on euro area exchanges between January 2014 and April 2024 [2]. Credit spreads are then calculated as the difference between corporate bond yields and the maturity-matched implied risk-free rates. For the euro area, German government bonds are commonly used as a proxy for the risk-free rate. I approximate the risk-free rate using the term-structure-implied interest rate on German federal securities for a given maturity. The Bundesbank provides synthetically constructed rates on federal securities for maturities of up to 30 years using the method of Svensson (1994).

Credit spreads reflect both firm-specific credit risk and investors' willingness to hold riskier and potentially less liquid corporate bonds. Following Gilchrist and Zakrajšek (2012) credit spreads can therefore be further decomposed into a fundamental default risk component and the excess bond premium. To decompose the spread into the two components, a measure of default risk is needed. Gilchrist and Zakrajšek (2012) estimate a measure for the probability of default using a Merton (1974)-type model. As a measure of firm default risk, I rely on the daily 5-year probability of default (PDs) for the issuing firms from Bloomberg. PDs measure the probability of a firm default over a 5-year horizon using a similar Merton (1974)-type model. A default occurs in this model whenever the value of a firm's assets, derived from the market value of the firm's equity, drops below a threshold value, where the firm's liability structure determines the default point. This measure of default risk is, therefore, constructed as a combination of company fundamentals and market-derived factors, calculated on a daily basis.

The logarithm of the credit spread $s_{ik,t}$ of firm i and bond k at time t is regressed on the measure of the firm's default risk $PD_{i,t}$ as well as on the remaining duration

[2] All bonds available on Datastream that are traded on the following stock exchanges are included: Frankfurt, Paris, Luxembourg, Dublin, Amsterdam, Brussels, Vienna, Munich, Stuttgart, Milan, Athens, and Helsinki.

of the bond $DUR_{i,k,t}$:

$$log(s_{ik,t}) = \alpha_{ik} + \beta_{ik} PD_{i,t} + \gamma_{ik} DUR_{i,k,t} + \epsilon_{ik,t} \tag{1}$$

The daily frequency of the data allows this regression to be performed on bond level. This ensures that other time-invariant bond characteristics are appropriately captured in the default risk component and implies that time-invariant yield differences between bonds are fully attributed to the fundamental risk component. To ensure sufficient data for each regression, the sample is restricted to bonds outstanding for at least 100 days over the sample period. The explained part of $\hat{s}_{ik,t}$ captures fundamental firm default risk, while the residual $e_{ik,t} = s_{ik,t} - \hat{s}_{ik,t}$ captures the risk premium.

The individual spread and its components are calculated on the bond level. The estimates for the spread of bond k issued by firm i in industry or country j and its components are aggregated to a euro-area credit market index as the unweighted average ($w_{ik,t} = \frac{1}{\#bonds}$) following Gilchrist and Zakrajšek (2012) (Equation 2). Industry and country aggregates, which in some cases only consist of a few bonds, are aggregated as a weighted average, where weights are determined by the issuance volume ($w_{ik,t} = \frac{volume_{k,t}}{outstanding_{j,t}}$). The final unbalanced sample of bonds includes 1364 bonds issued by 366 firms. The total number of NFCs included in the sample is comparable to other previous studies for the euro area (Gilchrist and Mojon, 2018). However, coverage is significantly better for the last years of the sample than for the early years (Online Appendix A.1, Table A2). Estimations are therefore performed over the whole sample from January 2014 to April 2024 and over a shorter subsample covering the full-scale invasion of Ukraine from January 2022 onward. The availability of daily data ensures sufficient observations also for the sample starting in 2022. Moreover, the shorter subsample encompasses the majority of sanction events. Decompositions of spreads across industries, countries, and spread components will, therefore, be performed for the subsample starting in 2022. Nonetheless, even for the early years, sufficient bonds are available to construct an aggregate spread index. The availability of spread data further poses no threat to the identification approach of the sanction shock even in early periods, as the index composition is not affected by the events under investigation. Further details on the sample of bonds, the calculation of credit spreads, and summary statistics are given in Online Appendix A.1.

$$s_{(j),t} = \sum_{ik \in j} w_{ik,t} s_{ik,t} \qquad \hat{s}_{(j),t} = \sum_{ik \in j} w_{ik,t} \hat{s}_{ik,t} \qquad e_{(j),t} = s_{(j),t} - \hat{s}_{(j),t} \tag{2}$$

2.2. Data on sanction and countersanction announcements

To measure the sanction intensity shock, announcement days of sanction and countersanction measures by the EU and Russia over the war in Ukraine are collected from official sources. First sanctions and countermeasures were imposed after the Russian annexation of Crimea in February and March 2014. After the full-scale invasion of Ukraine in 2022, the EU adopted 13 sanction packages against Russia over the sample period. The identification approach requires the announcement days on which restrictive measures against Russia over the war in Ukraine were taken. For the EU, the announcement days of restrictive measures are retrieved from the official website of the European Council [3]. For Russia, multiple official websites are used to collect countersanction measures. In total, the EU and Russia have announced (counter)sanction measures over Ukraine on 44 individual days over the considered sample period. Rigobon (2003) proves that the estimates remain consistent under potential misspecification of event days. Estimates do, however, become less precise as the differences between the two regimes diminish. Here, only official announcements of sanction and countersanction measures are used for identification. This suggests that by construction other days on which information regarding the sanction probability and design becomes public are not included. However, as long as more information regarding sanctions becomes public on announcement days compared to non-announcement days on average, the identification approach is applicable. This is also tested empirically. Further background information on the conflict and an overview of all sanction and countersanction announcements is given in Online Appendix B.1 (Table A8) [4].

I further collect financial and news variables for the structural VAR estimation of the sanction shock. To identify the sanction shock, variables sensitive to the conflict need to be selected. I include the Stoxx Europe 600 index to capture equity price movements, the VIXIE index, which is the iTraxx/CBOE 1-year implied volatility index for European credit markets, the GPRD geopolitical risk index of Caldara and Iacoviello (2022), and front-month TTF gas prices for the EU. Logarithmic transformations are applied to the GPRD, the Stoxx Europe 600, and the VIXIE index, as well as to the TTF gas prices. Summary statistics for all series are provided in Online Appendix A.2 (Table A3). Lastly, firm financial data on a quarterly frequency between 2014 Q1 and 2024 Q1 is collected from S&P Capital IQ for firms located in the EU. These variables include corporate leverage, defined as the share of total

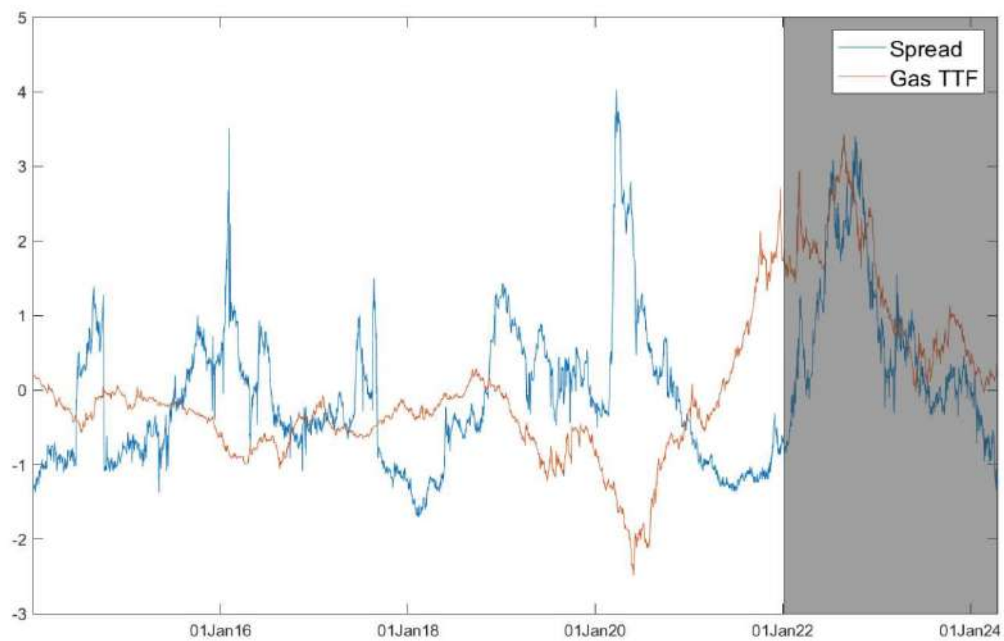
[3] Sanction timeline

[4] If the sanction announcement is made on a weekend, the following day with available financial data is selected.

outstanding debt to total equity, EBIT, and firm investment, calculated as the logarithmic difference in firms' tangible capital (net Property, Plant, and Equipment). Summary statistics of firm financials are reported in Online Appendix A.2 Table A4.

Over large parts of the sample period, credit spreads and gas prices in the EU show a negative correlation (Figure 1). Most strikingly, the economic downturn due to the COVID-19 pandemic in 2020 led to a sharp spike in credit spreads and a strong decline in gas prices as demand dwindled. The contemporaneous cross-correlation between the two daily series between January 2014 and January 2022 was as low as -0.56. After the start of the Russian invasion of Ukraine in early 2022, EU gas prices and credit spreads started to move in parallel (correlation: 0.76). At the same time, the correlation between daily gas prices and the daily geopolitical risk index of Caldara and Iacoviello (2022) rose from 0.05 to 0.16. This paper exploits such changes in the variance-covariance structure of financial and news variables around sanction announcements to identify sanction intensity shocks and to estimate the impact of sanction shocks on corporate credit spreads, firm default risk, and the excess bond premium.

Figure 1: Credit spreads and gas futures (2014 to 2024)



Notes: Credit spread and the log-transformed front-month TTF gas future price (standardized). Daily data between January 2014 and April 2024 collected from Datastream. The shaded area corresponds to the period of intensified conflict starting in 2022.

2.3. Firm-level data on Russia exposure

To identify companies highly dependent on Russia, the measure of Hassan et al. (2024), derived from analyst call transcripts, is used. Exposure to Russia can take multiple forms: Firms differ in their reliance on Russian energy and commodities for production, their dependence on the Russian market for exports, their reliance on the openness of the Russian airspace, or their direct investment in the country among others. This suggests that no single direct measure can adequately reflect firm-level exposure. Therefore, relying on a derived measure based on investors' concerns raised during analyst calls before the invasion gives a multifaceted view on firm-specific country risk.

The measure of country risk of Hassan et al. (2024) is computed on a firm-country-quarter level for a large sample of listed firms in the EU. It measures the fraction of time devoted to risks related to a specific country in a firm's analyst conference calls. As investors are free to raise questions about any risks for a firm's business model during such calls, this gives a good indication of the perceived reliance of a firm on a given country by investors[5]. For each firm in the sample, I compute the average Russia-related risk over 2019 and 2020 (8 quarters), the last two years of available data. A high risk measure indicates that a firm's investors were concerned with Russia-related risk before the full-scale invasion of Ukraine. Firms grouped as having a high Russia risk include Renault, generating around a tenth of its global revenue in Russia before the war, or RWE, a German energy company relying for around a third of its electricity production in 2021 on natural gas[6]. The full list of firms grouped as having a high exposure is given in Online Appendix A.2, Table A5.

3. Official sanction announcements, sanction intensity, and corporate credit spreads

As a first step, I verify that the selected official sanction announcement days are indeed characterized by elevated sanction intensity. If all details of the sanctions were already known to the public in advance of the official announcements, the selected days would not be informative and no inference regarding their effects could be drawn. To verify that official announcement days were indeed days characterised by a prominent discussion of sanctions in the public sphere, I construct a new index capturing the number of articles mentioning "sanctions", "Russia", and "Ukaine" on

[5]Please refer to the original paper for details on the calculation and validation of the risk metric: https://doi.org/10.1093/restud/rdad080

[6]Statista, Politico

a given day. I focus on sources with a high publication speed available on Factiva, namely Reuters Newswire, Dow Jones Newswire, and the Wall Street Journal. Duplicate articles are manually excluded from the count. I construct the index for the year 2014 as well as for the period from January 2022 to the end of the sample, capturing all but three new sanction announcements. Official sanction announcement days and newspaper coverage of sanctions are plotted together in Figure 2. Reassuringly, the selected days of official announcements also correspond to days in which the public discussion of sanctions was most prominent. Several of the announcement days fall on or around local maxima of the news index. This shows that even after the annexation of Crimea and the full-scale invasion of Ukraine in March 2014 and February 2022, respectively, new sanction packages were followed closely by the public.

To confirm also econometrically that the selected days are characterised by a high sanction intensity, I run a simple regression model

$$intensity_t = \alpha + \beta announcement_t + \epsilon_t \tag{3}$$

where $announcement_t$ is a dummy variable taking the value one on days of official sanction announcements and the value zero on other days. Sanction *intensity* is proxied by the sanction news index, the daily GPR index, and the TTF gas price (all log-transformed).

Moreover, I test whether additional and new information regarding the sanctions is made public on the selected days. For that purpose, I run additional regressions of the form:

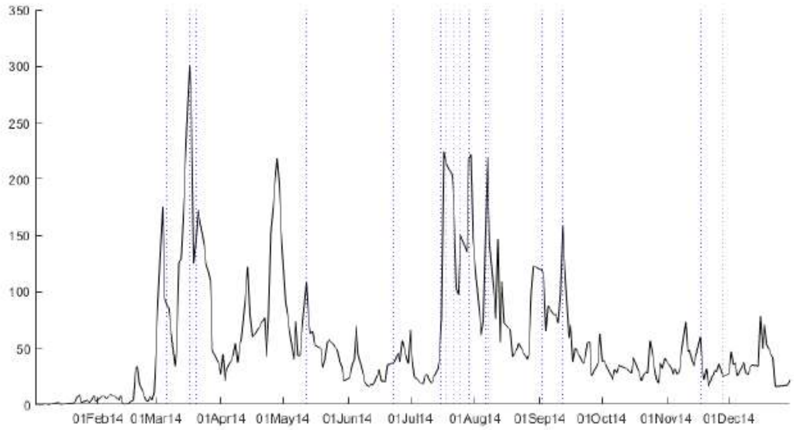
$$\Delta intensity_t = \alpha + \beta announcement_t + \epsilon_t \tag{4}$$

If all information was perfectly anticipated by the public and gas market participants, no movement in sanction intensity would be expected. In this setting, I focus only on the series capturing new information regarding the conflict at hand, namely the sanction index and gas price volatility. The directional change of gas prices on announcement days is uncertain. If sanctions turn out stricter than anticipated, increasing the risk of supply disruptions, gas prices are expected to increase. If, on the other hand, the announced sanctions are less severe or successful in mitigating the risk of supply disruptions, prices might decline. However, if the selected days are days of higher-than-usual information content on sanction design and likelihood, movements in gas prices on these days are expected to be larger in size. Therefore, I include the realized volatility of gas prices defined as $\sigma^2_{TTF} = r^2_{TTF}$.

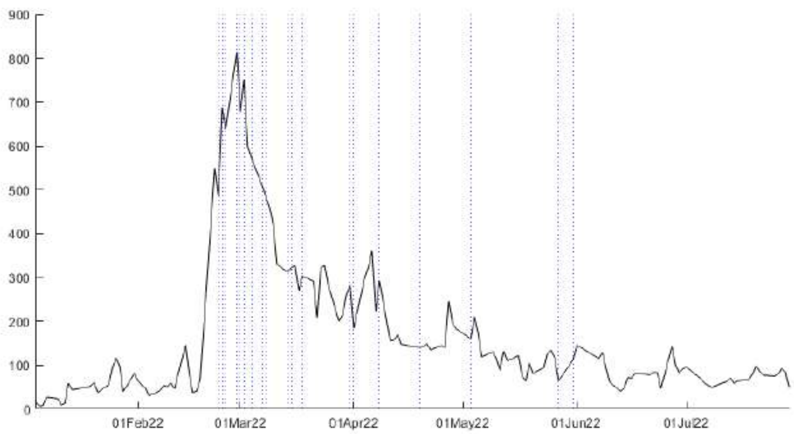
Columns 1-3 in Table 1 show that the selected event days are indeed days of elevated sanction intensity. On official announcement days, sanctions are covered

Figure 2: Official sanction announcements and the coverage of sanctions in the news

(a) 2014



(b) 2022



Notes: The black line shows the number of articles mentioning sanctions, Russia, and Ukraine in the Dow Jones Newswire, Reuters Newswire, or the Wall Street Journal. The interrupted blue lines indicate official (counter)sanction announcement days.

multiple times more often in the news, and geopolitical risk and gas prices are substantially higher. Columns 4 and 5 further confirm that announcements contain important signals on the conflict. Sanction coverage in the news increases further by around 10 percent. Moreover, high gas price volatility confirms that commodity traders incorporate new information. The approach to identify sanction intensity shocks in a structural VAR will exploit the finding of increased gas price volatility on announcement days.

Table 1: Official sanction announcements and sanction intensity

	(1) Sanction news	(2) GPRD	(3) TTF gas price	(4) Δ Sanction news	(5) σ^2_{TTF}
announcement	1.520***	0.604***	0.754***	0.099*	0.016**
	(0.161)	(0.083)	(0.136)	(0.059)	(0.007)
Observations	793	2512	2512	788	2511
R^2	0.122	0.034	0.017	0.002	0.046

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: A logarithmic transformation is applied to all dependent variables. The sanction news index captures the year 2014 as well as the period following the full-scale invasion in 2022.

Before turning to the identification of a sanction intensity shock in a full structural VAR, I estimate the effect of sanction announcements on euro area corporate credit spreads in a panel local projection setting. In particular, I test whether the announcements led to an increase in spreads and its components (Equation 5) and whether the increase was stronger for EU firms highly-exposed to Russia (Equation 6):

$$\Delta_h s_{ik,t+h} = \beta^h announcement_t + \alpha^h_{ik} + \epsilon_{ik,t+h} \tag{5}$$

$$\Delta_h s_{ik,t+h} = \beta^h_1 announcement_t + \beta^h_2 announcement_t * high\_RU\_exp + \alpha^h_{ik} + \epsilon_{ik,t+h} \tag{6}$$

Under the assumption that the sanction announcement days are purely determined by the underlying conflict and not related to credit spreads in any other meaningful way, the coefficient yields the effect of the unanticipated part of the announced measures on corporate spreads. If measures were fully anticipated, announcements should not affect corporate credit spreads. Table 2 shows an immediate increase in corporate credit spreads around sanction announcements, reaching around 5 basis points after five business days. The EBP captures the largest share of the increase, explaining around three-quarters of the increase after five business days and two-thirds after ten days.

Table 2: Official sanction announcements and corporate spreads

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		h=1			h=5			h=10	
	Spread	EBP	Default risk	Spread	EBP	Default risk	Spread	EBP	Default risk
announcement	0.017***	0.014***	0.003**	0.053***	0.040***	0.013***	0.047***	0.031***	0.016***
	(0.003)	(0.004)	(0.001)	(0.006)	(0.008)	(0.003)	(0.006)	(0.007)	(0.002)
Observations	1463467	1463467	1463467	1458011	1458011	1458011	1451191	1451191	1451191
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table examines the effect of sanction announcements on corporate spreads in a panel regression setting covering the period from January 2014 to April 2024. The dependent variable is the credit spread over various horizons (1, 5 and 10 days ahead).

Interestingly, firms classified as having a high Russia exposure experience a stronger increase in their spreads by around 1-2 basis points (Table 3). These results suggest that sanction announcements affect corporate financing costs, in particular in the case of large corporate risk exposures. However, announcement days might vary in the severity of the imposed measures, and some information regarding sanction design might become public on alternative days. The following section presents a structural approach to the identification of daily sanction intensity shocks and their effect on corporate spreads.

Table 3: Official sanction announcements, firm-specific Russia dependence, and corporate spreads

	(1)	(2)	(3)
	Spread	Spread	Spread
	h=1	h=5	h=10
announcement	0.011***	0.044***	0.047***
	(0.001)	(0.005)	(0.004)
High RU risk × announcement	0.009***	0.021**	0.025
	(0.002)	(0.007)	(0.014)
Observations	773887	770875	767110
Bond FE	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table examines the effect of sanction announcements on corporate spreads and its components in a panel regression setting covering the period from January 2014 to April 2024. Firm-specific Russia dependence is measured by the index of Hassan et al. (2024). The dependent variable is the credit spread over various horizons (1, 5 and 10 days ahead).

4. Methodology: A structural VAR to identify sanction intensity shocks

The impact of sanction intensity shocks on euro-area corporate credit spreads is estimated in a structural VAR, identified through event-day heteroskedasticity. Boer et al. (2023) propose this identification approach to estimate the impact of trade policy shocks on US and international stock prices. This methodology is similarly suited to investigate the impact of sanction and countersanction announcements on euro area credit spreads and fundamental corporate default risk.

The structural VAR includes the credit spread index, equity prices, the GPRD index, front-month gas future prices, and implied credit market volatility. Equation 7 describes a reduced form VAR with intercept μ, where Y_t is a vector collecting the five variables of interest, $A(L)$ is a collection of parameters for the selected lags, and reduced form errors are collected in the vector u_t.

$$A(L)Y_t = \mu + u_t \tag{7}$$

By selecting event days, on which a higher variance of the sanction shock is expected, the shock is identified.

The identification relies on two major assumptions: First, the variance of the sanction shock is assumed to be larger on sanction and countersanction announcement days than on other days. Second, all other shocks are required to have a constant variance across all dates. The first assumption imposes that new and relevant information on the design of sanctions becomes public on announcement days. While the individual restrictive measures did not come unanticipated to the public, their precise scope was subject to confidential debate among country leaders before their announcement. This is reflected in the documented increase in sanction intensity on official announcement days. The second assumption requires that no other fundamental shift in the shock variances occur between the subsamples of announcement days and non-announcement days. To ensure that no other events unrelated to the EU-Russia conflict drive the results, I perform multiple robustness checks. I remove days of ECB monetary policy decisions, days of other economic events, and days of relevant economic data releases coinciding with (counter)sanction announcement days, from the event sample and results remain unchanged (Online Appendix B.3). One advantage of the identification approach is that both assumptions can be tested empirically. Lastly, identification requires the untestable but common assumption that the impact of the sanction shock b_1 is constant across all dates.

The selection of event days and variables are the only identification decisions needed and no further restrictions are applied. Sanction shocks are then identified using differences in the covariance matrices of the financial and news variables between announcement and non-announcement days. This approach is comparable to an event study setting, while not requiring sanction announcements to be unanticipated. Moreover, embedding the identification in a VAR setting allows for dynamic feedback loops between variables without imposing exclusion restrictions. Following Boer et al. (2023), I select a lag order of 5 days as the baseline specification for all model estimations. The results are, however, robust to other specifications (Online Appendix B.6) . Reduced form errors u_t are linearly related to the orthogonal structural shocks ϵ_t through matrix B s.t. $u_t = B\epsilon_t = \sum_{i=1}^{k} b_i \epsilon_{t,i}$. Without loss of generality the sanction shock can be ordered first, as no short-run restrictions are required for the identification approach. Assuming that the sanction shock has variance $\sigma_{\mathbf{1}}^{\mathbf{2}}$ on announcement dates and variance $\sigma_{\mathbf{0}}^{\mathbf{2}}$ on non-announcement days, the covariance matrix $\Sigma_{\mathbf{1}}$ of the reduced form errors on announcement days is:

$$\Sigma_{\mathbf{1}} = \mathrm{E}\left(u_t u_t'\right) = \mathrm{E}\left(B\varepsilon_t \varepsilon_t' B'\right) = b_{\mathbf{1}} b_{\mathbf{1}}' \sigma_{\mathbf{1}}^{\mathbf{2}} + \sum_{i=\mathbf{2}}^{k} b_i {b_i}' \sigma_{\mathbf{i}}^{\mathbf{2}} \tag{8}$$

Subtracting the covariance matrix for non-announcement days we get the following expression assuming that all other shocks have a constant variance across announcement and non-announcement days:

$$\Sigma_1 - \Sigma_0 = b_1 b_1' \sigma_1^2 - b_1 b_1' \sigma_0^2 = b_1 b_1' \left(\sigma_1^2 - \sigma_0^2\right) \tag{9}$$

normalising the difference in the variance of the sanction shock to one provides us with a moment condition. We can minimize the following GMM objective

$$\hat{b}_1 = \underset{b_1}{\operatorname{argmin}}[\operatorname{vech}\left(\widehat{\Sigma_1} - \widehat{\Sigma_0} - b_1 b_1'\right)' \left(\frac{\widehat{V_0}}{T_0} + \frac{\widehat{V_1}}{T_1}\right)^{-1} \operatorname{vech}\left(\widehat{\Sigma_1} - \widehat{\Sigma_0} - b_1 b_1'\right)] \tag{10}$$

where $\widehat{V_0}$ and $\widehat{V_1}$ are sample estimates of the covariance matrices of $vech(\widehat{\Sigma_0})$ and $vech(\widehat{\Sigma_1})$. The first structural shock, namely the sanction shock, can then be extracted in the following way (Stock and Watson, 2018; Boer et al., 2023):

$$\epsilon_t^{sanction} = \frac{b_1' \Sigma_u^{-1} u_t}{(b_1' \Sigma_u^{-1} b_1)} \tag{11}$$

The assumption of heteroskedasticity in the sanction shock between announcement days and non-announcement days can be tested following Wright (2012) and Boer et al. (2023) using the following Wald test statistic:

$$\operatorname{vech}(\widehat{\Sigma_1} - \widehat{\Sigma_0})' \left(\frac{\widehat{V_0}}{T_0} + \frac{\widehat{V_1}}{T_1}\right)^{-1} \operatorname{vech}(\widehat{\Sigma_1} - \widehat{\Sigma_0}) \tag{12}$$

Similarly, the constant-variance assumption of all other shocks across event and non-event days can be tested using the test statistic minimised in Equation 10. For both tests, p-values are constructed using the distribution in bootstrapped samples based on the moving-block bootstrap of Jentsch and Lunsford (2019).

Two identification assumptions must be satisfied for the proposed methodology to capture sanction shocks appropriately. I test whether the variance of the first shock indeed significantly differs between announcement and non-announcement days (H0: $\Sigma_1 = \Sigma_0$). Moreover, I test whether the other shocks show a constant variance across the two sub-samples (H0: $\Sigma_1 - \Sigma_0 = b_1 b_1'$) against the alternative of multiple shocks on sanction announcement days (H1: $\Sigma_1 - \Sigma_0 - b_1 b_1' < 0$). Rejecting this hypothesis would imply that other factors change between announcement and non-announcement days, threatening the identification approach. Table A11 summarises the bootstrap-implied p-values for the two tests and for multiple model specifications. The results confirm that the sanction shock indeed shows a significantly higher variance on announcement days than on non-announcement days. Interestingly, the variance of the sanction shock does not differ significantly between the two samples before the start of the Russian invasion of Ukraine. This indicates that announcements of restrictive measures only led to a shift in the variance-covariance structure of the five variables after the start of the Russian invasion of Ukraine. The hypothesis of a single shock on announcement days is not rejected in any model specification. Online Appendix B.3 provides additional evidence for these assumptions in a less restrictive model environment, in which all shock variances are allowed to vary on announcement days.

Table 4: Test identification assumptions (p-values)

Sample	H0: $\Sigma_1 = \Sigma_0$	H0: $\Sigma_1 - \Sigma_0 = b_1 b_1'$
2014 to 2024	0.000	0.862
2022 to 2024	0.001	0.877
pre 2022	0.910	0.928

Notes: P-values derived from the bootstrapped distribution of the Wald test statistics given in Equation 12 (left column) and Equation 10 (right column). All observations are used in all samples to compute the variance-covariance matrices. A moving-block bootstrap of Jentsch and Lunsford (2019) is performed with 1000 repetitions. Following the authors, the block length is set at $l = 5 * T^{\frac{1}{4}}$ for each sample. Additional information on the implementation of the bootstrap is given by Boer et al. (2023).

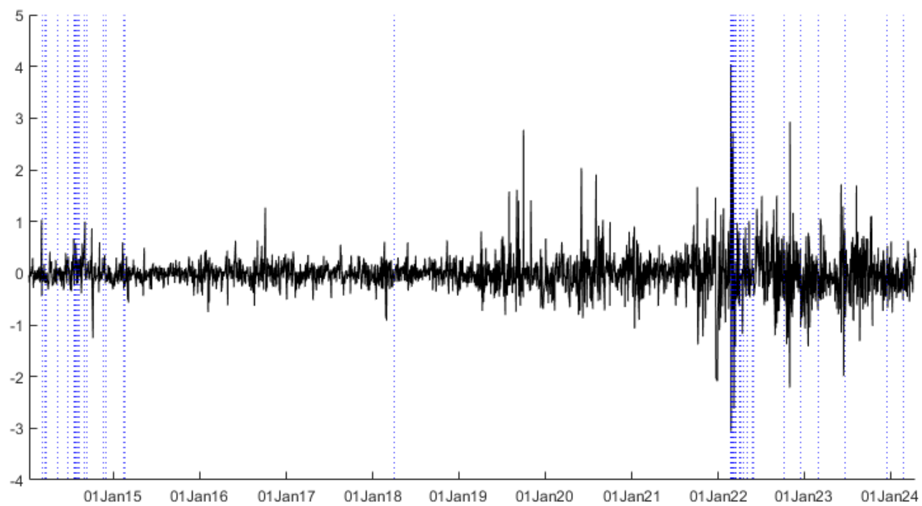
The methodology requires that only the shock variance changes between announcement days and non-announcement days, while the impact matrix B is assumed to stay constant. Recent advances have been made to test this assumption, which is prevalent throughout the VAR literature (Bruns and Lütkepohl, 2024; Lütkepohl and Schlaak, 2022). However, these approaches require alternative identification restrictions, such as long-run restrictions or alternative instruments unrelated to the heteroskedasticity of the shocks. Both are not available in the setting at hand. Given the daily frequency of the data, the assumption of constant coefficients is less restrictive than in comparable models at lower frequency. It merely assumes that a given sanction news affects the variables in the model on an announcement day in the same way as on a following non-announcement day. The underlying assumption, thus, imposes that no shifts in the relationship occur at the daily frequency between regimes.

5. The effect of sanction intensity on corporate credit spreads

5.1. Sanction intensity shocks and their effect on credit spreads

The sanction shock that results from the estimated model is depicted in Figure 3. The index peaks on the day of the Russian invasion of Ukraine on February 24, 2022, and shows high volatility after the start of the full-scale war with multiple spikes corresponding to sanction events. The first spike of the sanction index on March 3, 2014 coincides with the Russian annexation of Crimea and the first sanction measures taken by the EU. Sanction intensity measured after 2022 is substantially stronger than over the year 2014. The biggest spike in the sanction intensity index that is not observed in the proximity of sanction and countersanction announcements appears on October 1, 2019. On that day, Ukraine agreed to the "Steinmeier formula", which foresaw self-governing status and elections under Ukrainian law in the Donbass region. This decision was accompanied by strong protests in Ukraine and a spike in EU gas prices of above 40% on a single day. The two spikes in 2020 occur on June 6 and August 3 in the wake of the US election and amid mounting conflict over Northstream 2. On June 6, gas prices started to accelerate rapidly after reaching their trough over the sample period only a day earlier. The spike on August 3 likely reflects a statement by the then US Secretary of State Mike Pompeo on July 30 to do everything to stop the Northstream 2 project accompanied by another rise in gas prices of 30%. The resulting shock series, picking up days of elevated tensions and sanction intensity, can, thus, be interpreted as a EU-Russia geopolitical disintegration news shock. Major conflict events in the shock series are highlighted in Online Appendix B.1, Figure A1.

Figure 3: The sanction shock series



Notes: Daily sanction shock series extracted from the structural VAR including credit spreads, and the logarithmic transformation of the Stoxx Europe, the GPRD, the Gas TTF, and the VIXIE. Dotted lines correspond to the 44 (counter)sanction announcement days selected to identify the shock.

The shock series shows low cross-correlations with alternative measures of geopolitical risk and uncertainty, suggesting that the identified sanction shock captures EU-Russia specific events, rather than general changes in sentiment (Table 5). A stronger correlation can be observed between the sanction shock and the news-based EU gas supply shock of Alessandri and Gazzani (2025). Many of the events classified as gas supply shocks in their approach indeed correspond to EU-Russia specific geopolitical events, including sanction announcements. I verify that for all overlapping days, the underlying event was indeed directly related to sanctions and the war, ensuring that no other major gas supply events affect gas prices on announcement days. While they use geopolitical events to identify gas supply shocks looking solely at gas price changes, I exploit changes in the covariance of financial and news variables with gas prices on sanction announcement days to identify a sanction shock, measuring geopolitical and geoeconomic disintegration news. The comparably high correlation between the two shocks confirms that gas prices are sensitive to EU-Russia specific geopolitical events, making them a crucial component of the identification approach. The correlation also reflects that the supply of natural gas served Russia as a geopolitical policy tool against Europe because of Europe's dependence on Russian gas imports. The reduction in Russian gas supply to the EU, anticipated in gas future prices, can be interpreted as one important aspect of economic disintegration between the EU and Russia.

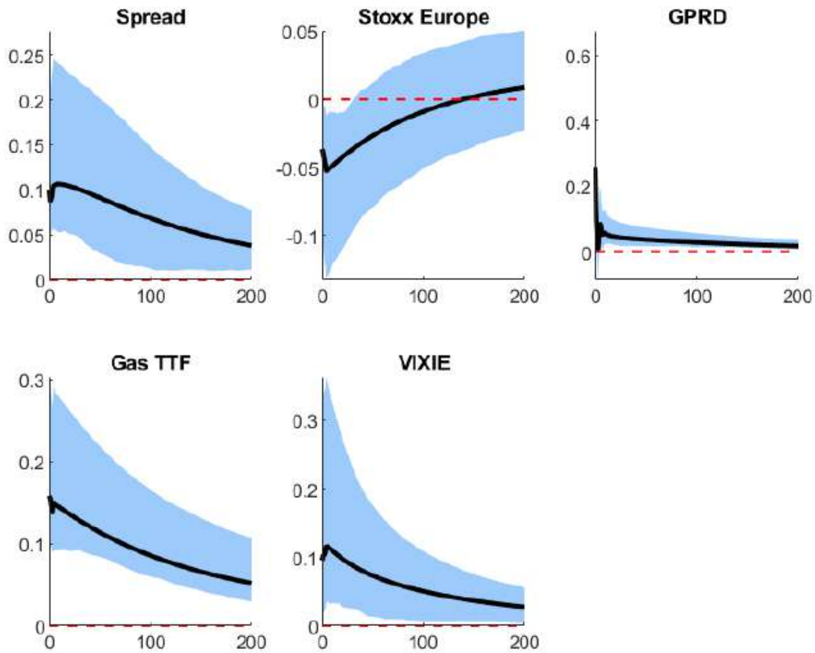
Table 5: Monthly cross-correlations with alternative shock series

Jan. 2014 - Dec. 2023	Sanction	GPR	GPR DEU	GPR FRA	EPU Europe	EU Gas
Sanction Shock	1	0.120	0.165	0.135	0.083	0.412
GPR		1	0.833	0.686	0.270	0.048
GPR DEU			1	0.596	0.262	0.088
GPR FRA				1	0.061	0.012
EPU Europe					1	0.081
EU Gas Shock						1
Jan. 2022 - Dec. 2023	Sanction	GPR	GPR DEU	GPR FRA	EPU Europe	EU Gas
Sanction Shock	1	0.203	0.277	0.257	0.221	0.472
GPR		1	0.817	0.886	0.247	0.285
GPR DEU			1	0.934	0.096	0.246
GPR FRA				1	0.060	0.287
EPU Europe					1	-0.037
EU Gas Shock						1

Notes: This table shows the monthly cross-correlation of the resulting sanction shock with alternative measures of geopolitical risk or general uncertainty. Country-specific and aggregate geopolitical risk indices (GPR) of Caldara and Iacoviello (2022), economic policy uncertainty (EPU) of Baker et al. (2016), and EU gas supply shocks of Alessandri and Gazzani (2025) are retrieved from the authors' websites.

Impulse response functions to an adverse sanction shock, as identified through heteroskedasticity and the (counter)sanction announcement days over the full sample period from 2014 to 2024, are shown in Figure 4. The impulse responses for the five variables included in the VAR correspond to a unitary sanction shock, reflecting the increase in the shock variance on announcement days. The impact effect of the shock on each variable of interest corresponds to the estimated coefficient b_1. Sanction shocks lead to a significant and economically meaningful increase in corporate credit spreads. A unitary sanction shock, corresponding to the increase in the shock variance on announcement days, leads to a rise in spreads of around 4 basis points. A shock of the size observed at the start of the Russian invasion of Ukraine is, thus, associated with an increase in the spread of 0.16 percentage points or around 8% relative to pre-war spread levels on aggregate. A sanction shock further leads to a decline in equity prices, a spike in the geopolitical risk index, substantially higher gas prices and heightened credit market volatility. Equity prices decline by around 0.4% after the unitary sanction shock while gas prices increase by around 12%. The effect on the credit spreads and gas prices is highly persistent and does not fully revert over a 200-day horizon. This indicates that EU-Russia sanction intensity induces correlation between EU spreads and gas prices, as suggested by Figure 1. Similarly, bond market volatility remains elevated over the whole horizon after a sanction shock.

Figure 4: Effect of a sanction shock on credit spreads, 2014 to 2024

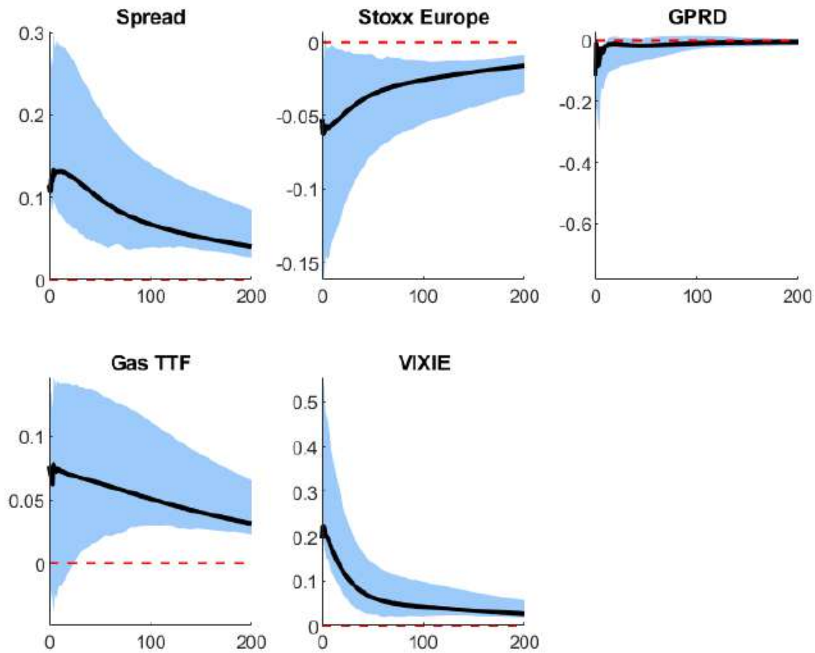


Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

To test whether the observed responses are merely driven by a shift from a period of relative peace before 2022 to a period of war in Europe after 2022, I estimate the impact of sanction and countersanction announcement shocks only for the subperiod starting in 2022. Again, similar responses of the financial variables are observed (Figure 5). The spike in spreads due to sanction intensity is even more pronounced for this shorter sample. This suggests that even within the period of conflict, announcement days of restrictive measures affected financial markets. Interestingly, the results remain comparable when removing the day of the start of the Russian invasion (February 24, 2022) from the event days. This suggests that these effects are not only driven by the beginning of the war but that individual sanction measures affect credit spreads.

Online Appendix B.2 explores the importance of including the TTF gas prices into the structural VAR model. The estimates of the variance-covariance matrices for the two regimes confirm that the main change in the variance-covariance structure

Figure 5: Effect of a sanction shock on credit spreads, 2022 to 2024



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 4, 2022 and April 15, 2024.

lies in the increased covariance of all financial and news variables with gas prices on announcement days (Online Appendix B.2 Tables A9, A10). The sensitivity of the EU gas prices to sanction intensity is, thus, crucial for the approach taken in this paper. The robustness of the results is further tested in a model including the component of gas prices orthogonal to the Brent oil price, thus, controlling for general commodity price movements between announcement and non-announcement days. Even in this restrictive setting all core results are confirmed (Online Appendix B.2 Figures A2-A4). The results are further robust to (i) removing days of monetary policy decisions and other important economic events as well as economic data releases (Online Appendix B.3 Figures A5, A7, and A6), (ii) a generalized model allowing all shocks to change variance on announcement days (Online Appendix B.4 Tables A12 and A13 and Figure A8), (iii) an alternative Proxy-VAR approach instrumenting sanction intensity with gas price changes on sanction announcement days (Online Appendix B.5 Figure A9), and (iv) to alternative lag lengths and placebo tests for randomly-scattered events (Online Appendix B.6 Figures A10, A11, A12, and A13). Lastly, the sanction intensity shock does not affect credit spreads of firms in EU countries shielded from sanctions through exemptions, such as Hungary and Slovakia, confirming that the shock indeed captures sanction intensity specifically rather than geopolitical risk more broadly (Online Appendix B.7 Figure A14).

5.2. Decomposition of the spread

The previous results established a strong response of credit spreads to EU-Russia sanction shocks. This could be driven by increased risk premia or by worsening firm prospects and higher corporate credit risk as firms suffer from sanction measures and trade fragmentation. To separate these two mechanisms through which sanction shocks can affect corporate financing costs on credit markets, I linearly decompose the effect of the sanction intensity shock on the spread. To do so, I estimate the response of the excess bond premium and the default risk component to a unitary increase in the sanction intensity shock, written as a linear projection model including the same set of controls X and lag order of 5 days. While regressing the components of the spread on a shock derived using the spread, among other variables, might seem counterintuitive at first glance, this is not fundamentally different to regressing rates and asset prices on monetary policy shocks, where exogenous high-frequency responses in these variables are used to derive the shock in the first place. Here, the exogenous shift is not identified using responses in tight intra-day windows but rather by the strength of covariance changes between variables on sanction announcement days:

$$\Delta_h EBP_{t+h} = \alpha^h + \beta_1^h \epsilon_t^{sanction} + \sum_{l=1}^{5} \beta_2^h X_{t-l} \tag{13}$$

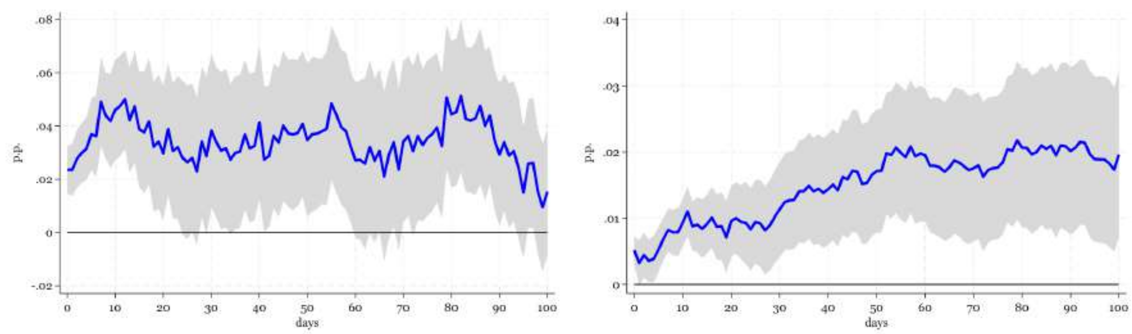
$$\Delta_h \hat{s}_{t+h} = \alpha^h + \beta_1^h \epsilon_t^{sanction} + \sum_{l=1}^{5} \beta_2^h X_{t-l} \tag{14}$$

The excess bond premium of the spread captures the risk-bearing capacity of financial intermediaries, while the default risk component reflects the fundamental risk in the issuing firm. Figure 6 shows a strong increase in both the default risk component and the excess bond premium of the spread after a sanction intensity shock. In this linear regression setting for the post 2022 period, the aggregate impact of the sanction shock on the spread reaches above 6 basis points. On impact, in particular the excess bond premium increases. After 20 days around three-quarter of the increase of the spread is explained by the excess bond premium. Over time, the effect on the default risk component strengthens considerably, contributing more than half of the increase in the spread after 100 days. The total impact on the spread is extremely persistent with high volatility in the excess bond premium component. This decomposition suggests that both the excess bond premium and the default risk component contribute to the increase in the spread. Different to other economic and financial shocks studied in the literature, the sanction shock leads to a significant response not only in the excess bond premium but also in the default component[7].

Figure 6: Effect of a sanction shock on the excess bond premium and the default risk component

(a) EBP

(b) Default risk



Notes: Decomposition of the response of the credit spread to a unitary sanction intensity shock together with the 90% confidence intervals. Controls include the logarithmically transformed Stoxx Europe, GPRD, Gas TTF, and VIXIE. Daily data between January 4, 2022 and April 15, 2024.

5.3. Comparison to alternative shocks

The resulting sanction shock, while derived using gas price movements, is in its effect on the corporate bond market more similar to a geopolitical risk shock than to a gas supply shock (Table 6). I perform a similar regression as before, regressing the change in the spread and the default risk component on various alternative monthly shock variables. Despite the low correlation of the sanction shock with the GPR, the two shocks have a comparable effect on spreads. Interestingly, however, the sanction intensity shock increases fundamental corporate default risk substantially more than the geopolitical risk shock. The gas supply shock of Alessandri and Gazzani (2025), while being correlated with the sanction shock, does not lead to a significant increase in the spread or the default risk component. This suggests, that

[7]Existing work suggests that responses of credit spreads to oil-, technology news-, and monetary policy shocks are primarily driven by liquidity and market sentiment rather than credit fundamentals (Chiţu et al., 2023; Boons et al., 2023; Anderson and Cesa-Bianchi, 2024).

the methodology chosen is successful in extracting the conflict- and sanction-specific information contained in gas price movements around sanction announcement days. This again confirms that the sanction shock is an exception in the literature in that it moves the default risk component of the spread.

Table 6: Comparison of the sanction shock to related shock series

	(1) Δ Spread	(2) Δ Spread	(3) Δ Spread	(4) Δ Spread	(5) Δ Default risk	(6) Δ Default risk	(7) Δ Default risk	(8) Δ Default risk
Sanction intensity	0.036**				0.018***			
	(0.018)				(0.006)			
EU gas supply		0.020				0.003		
		(0.017)				(0.005)		
GPR			0.030**				0.010*	
			(0.013)				(0.005)	
EPU Europe				0.027				0.008
				(0.020)				(0.010)
Observations	123	123	123	123	123	123	123	123
R^2	0.041	0.013	0.028	0.023	0.038	0.001	0.012	0.008

Standard errors in parentheses

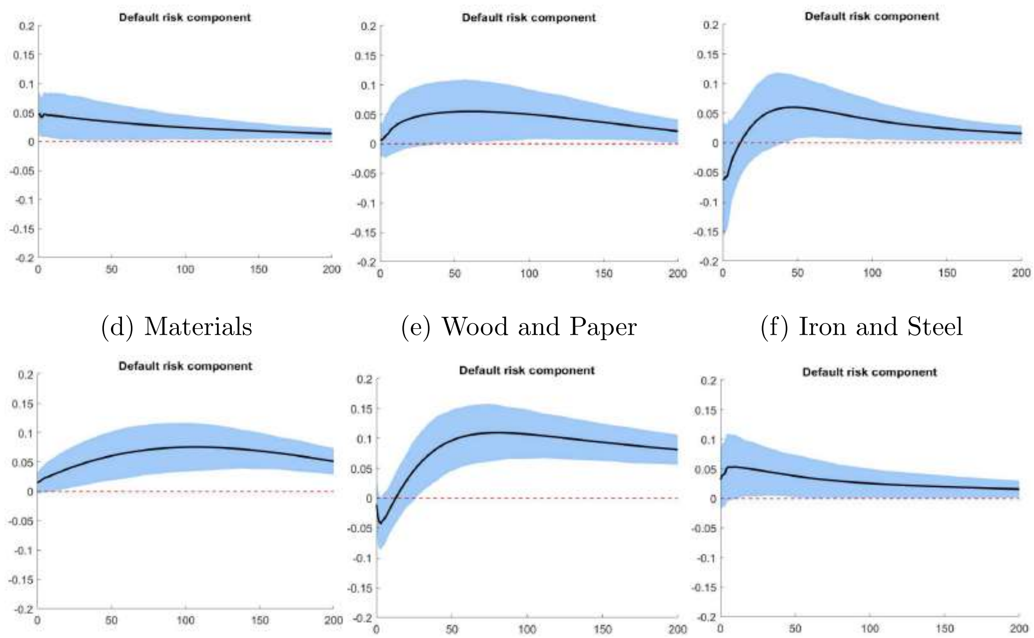
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Monthly data between January 2014 and April 2024. All shocks are standardized to have mean zero and unitary variance. Geopolitical risk index (GPR) of Caldara and Iacoviello (2022), economic policy uncertainty (EPU) of Baker et al. (2016), and EU gas supply shocks of Alessandri and Gazzani (2025) are retrieved from the authors' websites.

5.4. Heterogeneity across industries

To identify highly-affected industries, the VAR is again estimated, now including industry default risk indices rather than the aggregate spread. Figure 7 shows heterogeneous responses in the risk component across industries. Default risk rises for industries that have been major exporters to Russia before the war and that now fall under the sanction regime (Figure 7, top panel), as well as for industries in which Russia was a major exporter to the EU (Figure 7, bottom panel). Not surprisingly, precisely these industries also experience the strongest reduction in trade with Russia due to the sanction shock (Online Appendix C.2, Figure A23 and Figure A24). While the effect of sanction intensity on default risk is immediate for some industries (i.e. Car Manufacturers, Materials, Iron and Steel), other industries experience a delayed increase (i.e. Electrical Equipment, Machinery, Wood and Paper). However, not all industries are significantly affected by the EU-Russia conflict. Industries with a domestic focus (Construction, Telecommunication, etc.), industries not directly affected by the sanction regime (Healthcare, Pharmaceuticals, etc.), and industries that offer alternatives to energy imports from Russia (Energy - Alternate Source) appear less affected by the sanction shock (Online Appendix C.1, Figure A15).

Figure 7: Selected industries affected by sanction shocks



(a) Car Manufacturers (b) Electrical Equipment (c) Machinery

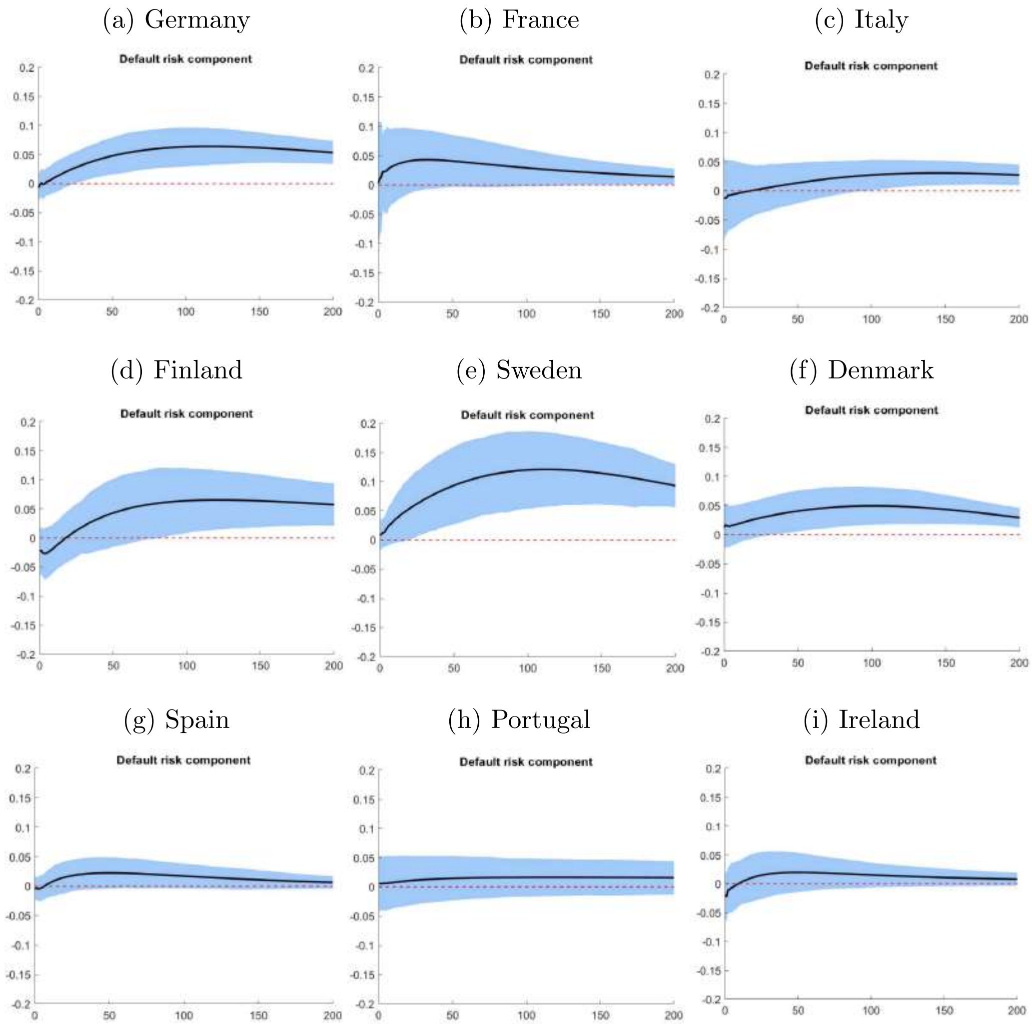
(d) Materials (e) Wood and Paper (f) Iron and Steel

Notes: Impulse response function to a one-standard-deviation sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. All variables are standardised to have a zero mean and a unit variance. Only industries for which at least three different firms have bonds outstanding at each point in time are depicted.

5.5. Heterogeneity across countries

Exposure to sanction intensity not only differs across industries but also across countries. Among the three major economies in the EU, Germany is affected strongest by the sanction shock (Figure 8). Germany maintained the strongest trade relationships with Russia before the invasion of Ukraine. Moreover, imports into key areas of the predominantly industrial German economy, such as energy and commodities for production, were highly concentrated from Russia. Similarly, the Scandinavian countries show a strong response to the sanction shock, likely reflecting geographic proximity. Countries in the western part of the EU with relatively little connections to the Russian economy show a low sensitivity to the shock. Impulse response functions for all industries and all countries in the sample are reported in Online Appendix C.1.

Figure 8: Selected countries



(a) Germany (b) France (c) Italy (d) Finland (e) Sweden (f) Denmark (g) Spain (h) Portugal (i) Ireland

Notes: Impulse response function to an adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. All variables are standardised to have a zero mean and a unit variance. Only countries for which at least three different firms have bonds outstanding at each point in time are depicted.

6. Firm-level effects of sanction intensity shocks

6.1. The effect of sanction intensity shocks across firm-level Russia risk

The effect of the sanction shock is expected to vary with firm-specific exposure to Russia controlling for industry or country dependencies. For that purpose, I classify firms according to their Russia-related risk and verify that highly exposed firms experience a stronger increase in borrowing costs. Different to the preceding structural VAR analysis for aggregate spread series, this analysis is performed on bond-level in a panel regression setting. I estimate this panel regression model for the cumulative change in the spread due to the sanction shock depicted in Figure 3 over various horizons. The sanction shock is further interacted with an indicator variable (*High RU risk*) taking the value 1 if a firm is in the highest quintile of Russia exposure and 0 otherwise. To ensure that this difference is purely driven by firm-specific Russia exposure, I further include interacted country-industry fixed effects, firm controls, and interactions of the sanction shock with firm controls. For this purpose, the bond data is combined with quarterly firm financials from S&P Capital IQ for firms registered in the EU. Firm leverage, defined as total debt over total equity, EBIT, interest expense, and total assets are included as control variables. Summary statistics for the corporate financial data are presented in Online Appendix A.2, Table A4.

The sanction shock significantly raises credit spreads, especially for firms with a high exposure to Russia (Table 7). This difference in the effect of sanctions on credit spreads between firms is significant over all four horizons. A unitary sanction shock is associated with an increase in the spread of around 2 basis points after two weeks for the less exposed firms, while the effect rises to around 2.7 basis points for the highly exposed firms accounting for country-industry exposure to Russia. Interestingly, a higher exposure to Russia is generally not associated with higher spreads besides the effect through the identified sanction shock. Economically stronger results are obtained for the sub-sample starting in 2022 (Online Appendix C.1, Table A15). These results confirm that investors, when responding to geopolitical news, price in firm-specific country exposure factors.

Table 7: Sanction impact for firms highly exposed to Russia

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-week ahead		2-weeks ahead		3-weeks ahead		4-weeks ahead	
	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
L.sanction_shock	0.014***	0.016***	0.019***	0.020***	0.018***	0.020***	0.016***	0.016***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
High RU risk	0.001**	0.000	0.001	-0.002	0.002	-0.004	0.003	-0.007
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)
High RU risk*L.sanction_shock	0.005**	0.005**	0.008**	0.007**	0.009***	0.006***	0.008**	0.006**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
N	582870	529126	577650	525549	574639	523928	574238	524717
Firms	162	162	162	162	162	162	162	162
Country FE	Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes	
Country-Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Controls*L.sanction_shock	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table examines the importance of firm-specific Russia dependence, measured by the index of Hassan et al. (2024), in a panel regression setting covering the period from January 2014 to April 2024. The dependent variable is the credit spread over various horizons (1, 2, 3, and 4 weeks ahead). Firms are classified as having a high Russia exposure if their Russia-specific risk index is above the 80th percentile on average in the years 2019 and 2020 (the last two available years before the full-scale invasion of Ukraine). Firm controls include total assets, EBIT, interest expenses, and leverage. Standard errors are clustered at the country level.

6.2. The effect of sanction intensity shocks across firm financials

The strength of the impact of sanction shocks on credit spreads and its components might not only depend on pre-sanction dependency of a firm on Russia, but also on firm financial fundamentals. The financial accelerator following Bernanke et al. (1999) suggests that financially constrained firms should experience a stronger increase in borrowing costs after negative shocks as agency costs rise. I test for heterogeneous effects of the sanction shock depending on firm leverage and earnings. In this setting, the traditional collateral borrowing constraint and potential earning-based borrowing constraints following Lian and Ma (2021) and Drechsel (2023) can be tested. For this purpose, firm leverage and EBIT are used separately to group firms dynamically into high-, medium-, and low-tertiles.

As before, the sanction shock is associated with a highly significant increase in credit spreads of around 4 basis points (Table 8). The excess bond premium and the default risk component rise significantly also in the panel regression setting after a sanction shock. Introducing interaction terms confirms collateral-based financial acceleration, whereby firms with high leverage close to the asset-borrowing constraint experience a stronger response in borrowing costs than firms with ample financing space. Financing costs for firms with high leverage rise by around 11 basis points more than for the average firm after a sanction shock. This is driven by a significantly stronger response of default risk and the excess bond premium to sanction intensity. The increase in the excess bond premium suggests that investors demand a higher premium for highly leveraged firms as sanctions can depress equity and collateral valuations. This result provides strong evidence for a collateral-based borrowing constraint.

Grouping firms according to earnings shows that the response of credit spreads and default risk to sanction shocks is also significantly stronger for firms with low EBIT levels. Firms with low EBIT levels face a 2.5 basis points stronger credit price response to sanction intensity than firms with high earnings. This effect is fully accounted for by the stronger increase in default risk. The response of the risk premium to sanctions, while partly mitigated for high-earning firms, does not strengthen for firms in the lowest-earning tertile. This suggests that the earnings-based borrowing constraint is not binding. An alternative and tighter model specification including firm fixed effects, thus isolating differences in the impact of the sanction shock on firms that change buckets over the sample period, again provides evidence for a binding collateral-based borrowing constraint only (Online Appendix C.1, Table A14).

Table 8: Firm financial space and sanction impact

	(1) Spread	(2) EBP	(3) Default risk	(4) Spread	(5) EBP	(6) Default risk	(7) Spread	(8) EBP	(9) Default risk
L.sanction_shock	0.042***	0.032***	0.010*	-0.003	0.020***	-0.023	0.038***	0.039***	-0.001
	(0.005)	(0.002)	(0.005)	(0.019)	(0.004)	(0.015)	(0.009)	(0.003)	(0.009)
Low leverage				-0.118	0.001	-0.119			
				(0.107)	(0.030)	(0.110)			
High leverage				0.544**	-0.013	0.557**			
				(0.252)	(0.016)	(0.256)			
Low leverage*L.sanction_shock				0.030	0.000	0.030			
				(0.030)	(0.008)	(0.023)			
High leverage*L.sanction_shock				0.109**	0.039***	0.071**			
				(0.040)	(0.011)	(0.030)			
Low EBIT							0.594**	0.013	0.580**
							(0.263)	(0.010)	(0.265)
High EBIT							-0.142**	-0.026**	-0.116**
							(0.051)	(0.012)	(0.047)
Low EBIT*L.sanction_shock							0.024**	-0.009	0.033**
							(0.011)	(0.006)	(0.013)
High EBIT*L.sanction_shock							-0.009	-0.011**	0.002
							(0.015)	(0.004)	(0.012)
N	663749	663749	663749	663749	663749	663749	663749	663749	663749
Firms	189	189	189	189	189	189	189	189	189
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table examines the importance of collateral- and earnings-based borrowing constraints in a panel regression setting covering the period from January 2014 to April 2024. The dependent variables are the credit spread and its components, the excess bond premium (EBP) and the default risk component. Firms are dynamically grouped into three equally sized bins according to their leverage and earnings levels. The intermediate bin is taken as a baseline. Standard errors are clustered at the country level.

6.3. *The impact of sanction intensity on firm investment*

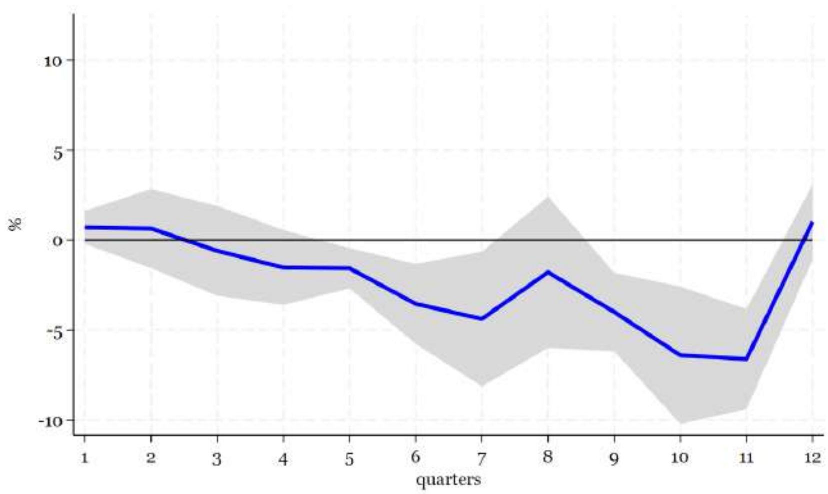
Sanction intensity, increasing corporate credit spreads and default risk, might lead to a reduction in new firm investment as borrowing costs rise, investment opportunities are constrained, and geopolitical uncertainty increases. Following Ottonello and Winberry (2020), I calculate firm investment as the log-difference in firm tangible capital (net PPE). I estimate panel local projections following Jordà (2005) for the impact of the sanction shock on firm investment using the same sample of firms. The following model specification is estimated:

$$\begin{aligned}\Delta_h Y_{i,t+h} =& \beta^h \epsilon_{t-1}^{sanction} + \sum_{j=1}^{3} \gamma_{1,j}^h \Delta Y_{i,t-j} + \sum_{j=1}^{3} \gamma_{2,j}^h \Delta X_{i,t-j} \\ &+ \gamma_3^h \epsilon_{t-2}^{sanction} + \gamma_4^h \epsilon_{t-3}^{sanction} + \alpha_c^h + \alpha_s^h + u_{i,t+h}\end{aligned} \tag{15}$$

$\Delta_h Y_{i,t+h}$ is the change in log-tangible capital, of firm i over horizon h, $\epsilon^{sanction}$ the sanction shock depicted in Figure 3 collapsed to a quarterly level, and $X_{i,t-j}$ firm controls. First differences of firm financials are included to control for time-varying firm characteristics besides changes in firm investment. Additionally, fixed effects for the country and industry are included. Lags of the sanction shock control for past developments in the shock of interest.

Firm investment declines for three years after the sanction shock (Figure 9). The cumulative decline in tangible capital reaches up to around 6 percent for a one standard deviation sanction shock and turns significant after around one year, reflecting the irreversibility and long-term nature of investment. The decline in corporate investment after sanction shocks is in line with the theoretical propositions of Gourio (2012) and supports the empirical findings of Caldara and Iacoviello (2022), which document reduced corporate investment after geopolitical risk shocks for exposed firms. The obtained impulse response is further robust to a tighter model specification including firm fixed effects (Online Appendix C.1, Figures A19).

Figure 9: Effect of a sanction shock on corporate investment



Notes: Impulse response function to a one standard deviation sanction shock with 90% (shaded area) confidence intervals. Standard errors are clustered at the country level. The black line depicts the coefficient β^h in Equation 15. Firm controls include total assets, leverage, EBIT, interest expenses, and the average corporate credit spread (all controls are included with first-differences).

To investigate whether the reduction in investment can be fully explained by elevated borrowing costs, I estimate an extended version of the panel local projection model. In the spirit of Gilchrist et al. (2014) I include the future path of the spread and the excess bond premium to control for any effects of the sanction shock on investment that can be explained by rising borrowing costs. We thus remove the effect of the shock on borrowing costs documented in the previous part of the paper. The results tell us whether the sanction intensity shock remains relevant for investment after accounting for the full information contained in credit spreads. In particular, I estimate two versions of the model. In the first specification only the contemporaneous borrowing costs are controlled for ($F = 0$). In the second specification the full path of borrowing costs up to the estimation horizon for investment is controlled for ($F = h$), removing any effect of the sanction intensity shock through future borrowing costs.

$$\begin{aligned}\Delta_h Y_{i,t+h} =& \beta^h \epsilon_{t-1}^{sanction} + \sum_{f=0}^{F} \gamma_{1,f}^h \Delta s_{i,t+f} + \sum_{j=1}^{3} \gamma_{2,j}^h \Delta Y_{i,t-j} + \sum_{j=1}^{3} \gamma_{3,j}^h \Delta X_{i,t-j} \\ &+ \gamma_4^h \epsilon_{t-2}^{sanction} + \gamma_5^h \epsilon_{t-3}^{sanction} + \alpha_c^h + \alpha_s^h + u_{i,t+h}\end{aligned} \tag{16}$$

Table 9 shows the direct effect of the sanction intensity shock on investment at its peak (after 10 quarters), accounting for borrowing costs in this reduced-form setting. Controlling for contemporaneous changes in the spread already reduces the peak effect of sanction intensity on investment by roughly 35% (column 2) from 6.6% to 4.3%. Including the excess bond premium instead of the spread reduces the effect even further by above 50% (column 3). The effect reduces by two-thirds when including the full path of the spread (column 4) and vanishes completely when including the full path of the excess bond premium (column 5). These results suggest that the sanction intensity shock reduces firm investment primarily through borrowing costs. In line with previous findings in the literature, the excess bond premium component of the spread captures the most important dimension of borrowing costs for firm investment. While this exercise provides some evidence that corporate credit spreads contain most of the information of the sanction shock for firm investment, a full decomposition of the various possible channels through which sanctions affect investment would need to be performed in a structural model.

Table 9: The effect of the sanction shock on corporate investment accounting for borrowing costs

	(1)	(2)	(3)	(4)	(5)
		F=0		F=h	
	$\Delta_h log(PPE)$	$\Delta_h log(PPE)$	$\Delta_h log(PPE)$	$\Delta_h log(PPE)$	$\Delta_h log(PPE)$
L.sanction_shock	-0.066***	-0.043***	-0.031***	-0.022**	-0.001
	(0.017)	(0.011)	(0.006)	(0.010)	(0.013)
ΔSpread		-0.217***		-0.178***	
		(0.014)		(0.014)	
ΔEBP			-0.315***		-0.244***
			(0.027)		(0.034)
N	1614	1614	1614	1614	1614
Firms	130	130	130	130	130
Controls	Yes	Yes	Yes	Yes	Yes
$\Delta Spread_{t+1}$ to $\Delta Spread_{t+h}$	No	No	No	Yes	No
ΔEBP_{t+1} to ΔEBP_{t+h}	No	No	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table examines the transmission of the sanction intensity shock to corporate investment through firm borrowing costs in a panel regression setting covering the period from January 2014 to April 2024. The dependent variable is the change in log-tangible capital for the peak of the sanction effect at $h = 10$. Borrowing costs are included as controls up to horizon F as laid out in Equation 16. Firm controls include the lagged total assets, leverage, EBIT, interest expenses, and the average corporate credit spread (all controls are included with first-differences). Standard errors are clustered at the country level.

7. Realized bankruptcies after sanction intensity shocks

One key feature of the identified sanction intensity shock is its effect on corporate default risk. However, sanction intensity might not only be reflected in the derived corporate default risk using financial market data, but might also be realized in the form of observed corporate bankruptcies. To analyze such a potential effect, the sanction shock series (Figure 3) is aggregated to a monthly frequency. Local projections, including the sanction shock, bankruptcy rates, and country controls are estimated. Data on bankruptcy rates by country and industry are collected from Eurostat. Lastly, country data on consumer prices, industrial production, 10-year sovereign bond yields, and the nominal effective exchange rate are collected. An overview of the variables and summary statistics are given in the appendix (Online Appendix A.3, Tables A6 and A7).

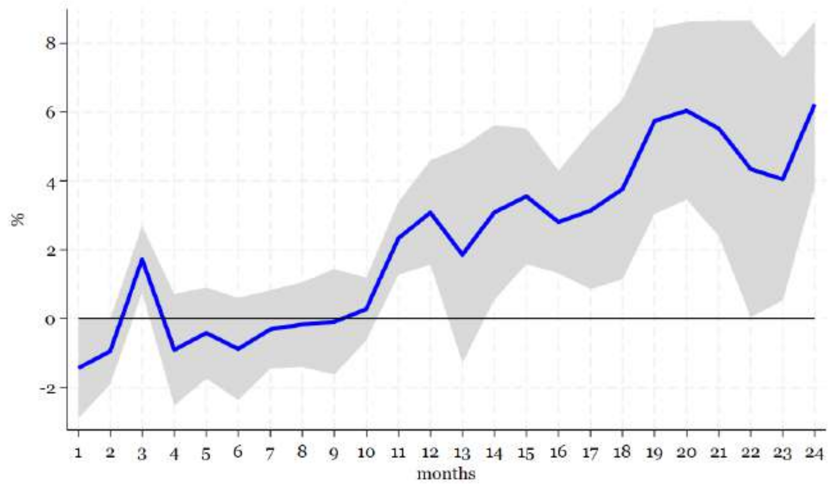
I estimate the impact of the sanction shock on bankruptcies using a panel local projection model for aggregate statistics. I include the logarithmically-transformed bankruptcy index for industry s and country c as dependent variable $Y_{s,c,t+h}$ and estimate effects over various horizons h. The main coefficient of interest is the coefficient β^h of the average monthly sanction shock lagged by one month ($\epsilon_{t-1}^{sanction}$). To control for time-varying country characteristics, first-differences of the four country controls $\Delta X_{c,t-j}$ are included with lags up to 3 months. To properly measure the effect of innovations in the sanction shock, I further control for past developments in the dependent variable and in the sanction shock. Moreover, country and sector fixed effects α^h and a month indicator $\alpha_{m(t)}^h$ to control for seasonality are included in the regression. Standard errors are clustered at the country level.

Aggregating well-identified higher-frequency shocks to a lower frequency to analyze their relationship with aggregate macroeconomic variables is a common practice in the monetary policy literature. The underlying assumption is that if shocks are truly exogenous at the high frequency, they should remain exogenous also at the lower frequency. However, in the context of the very volatile macroeconomic and financial environment after the full-scale invasion of Ukraine, we cannot rule out the possibility that monthly sanction intensity correlates with other economic developments at the time. To account for this possibility, I confirm the robustness of the result to additionally including a number of alternative shock series. I include three lags of the GPR index, the European EPU index, euro area monetary policy shocks of Jarociński and Karadi (2020), and gas price shocks of Alessandri and Gazzani (2025). In a further exercise, I remove the period of the COVID-19 pandemic to ensure that results are indeed responses to the sanction shock. Results remain qualitatively unchanged by the inclusion of these additional controls and the removal of the COVID-19 period and are reported in the Online Appendix C.2.

$$\begin{aligned}\Delta_h Y_{s,c,t+h} =& \beta^h \epsilon_{t-1}^{sanction} + \sum_{j=1}^{3} \gamma_{1,j}^h \Delta Y_{s,c,t-j} + \sum_{j=1}^{3} \gamma_{2,j}^h \Delta X_{c,t-j} \\ & + \gamma_3^h \epsilon_{t-2}^{sanction} + \gamma_4^h \epsilon_{t-3}^{sanction} + \alpha_s^h + \alpha_c^h + \alpha_{m(t)}^h + u_{s,c,t+h}\end{aligned} \tag{17}$$

Cumulative impulse response functions of the bankruptcy index to the sanction shock are depicted in Figure 10. The sanction shock is associated with a strong increase in bankruptcies after 10 months. Bankruptcies continue to rise over the second year after the shock and reach an increase of 6% relative to the base month after 24 months. This effect is highly significant and economically meaningful.

Figure 10: Effect of a sanction shock on bankruptcy rates



Notes: Impulse response function to a one standard deviation sanction shock with a 90% confidence interval. Standard errors are clustered at the country level. The black line depicts the coefficient β^h in Equation 17. Country controls include the logarithmically transformed industrial production and CPI and the 10-year sovereign bond yield and net effective exchange rate (all controls are included with first-differences). Monthly data between January 2015 and December 2023 (bankruptcy data available from 2015 onward only).

In the second step, I include sector interactions with the sanction shock to allow for heterogeneity in industry responses. All sectors show a similar tendency of rising bankruptcies after 10 months (Online Appendix C.2, Figure A21). Not all countries report bankruptcy data on a monthly frequency in Eurostat. As a robustness check, an alternative model specification using quarterly bankruptcy data for a larger sample of 18 EU countries is estimated. The results confirm the strong effect of sanction intensity on bankruptcy filings after one year and across industries (Online Appendix C.2, Figure A22). These results confirm that not only default risk, as derived from financial markets, responds to the sanction intensity, but also that observed bankruptcies increase.

These results suggest that the sanction shock, identified in a high-frequency setting using sanction and countersanction announcement-day heteroskedasticity, also translates into observed corporate credit risk. The number of bankruptcies is elevated after ten months of a sanction intensity shock and increases thereafter.

8. Conclusion

How does geopolitical fragmentation affect firm riskiness and corporate financing conditions? Which firms are particularly vulnerable? Do we see that the EU-Russia conflict affected the credit market and firm outcomes? These are the questions that I addressed in this paper. These questions are particularly relevant in the context of the recent proliferation of geoeconomic power struggles. This paper approaches these questions using a novel identification of sanction intensity shocks, exploiting sanction and countersanction announcements by the EU and Russia between 2014 and 2024.

The paper documents that sanction intensity leads to elevated corporate credit spreads and default risk. In particular, firms, industries, and countries with a high pre-war dependence on Russia show a deterioration in credit risk. Firms with high leverage levels face a higher risk premium due to sanction intensity, suggesting a collateral-based borrowing constraint. The effect of sanction intensity on firms is not only reflected on financial markets but spills over to the real economy in the form of dampened investment levels and rising bankruptcies. Future work could quantify the channels through which sanction intensity affects corporate investment decisions in a structural model.

In an environment of intensifying geopolitical conflicts, this paper puts corporate vulnerabilities to economic and geopolitical fragmentation in the spotlight. The results suggest that vulnerability differs greatly across industries, countries, and firms. These results emphasize the threats to financial and economic stability from geoeconomic dependence once sanctions are imposed, which need to be managed and controlled. Firms and policy makers have to understand these threats to increase resilience and to navigate through global conflicts.

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Online Appendix for "Geopolitics and corporate credit risk: Evidence from EU-Russia sanction shocks"

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Appendix A. Sample details

Appendix A.1. Bond sample

Table A1: Summary statistics - bond sample

	P25	Median	P75	Mean	SD	N	Firms	Bonds
Issuance amount	400 000 000	500 000 000	750 000 000	578 160 783	333 568 002	1562575	366	1364
Duration	4.04	6.07	8.52	6.70	3.78	1562575	366	1364
Excess Bond Premium	-0.22	-0.04	0.17	0.01	1.41	1562575	366	1364
Default risk component	0.99	1.30	1.94	2.13	4.13	1562575	366	1364
5y PD	0.01	0.02	0.03	0.03	0.04	1562575	366	1364
Spread	0.93	1.30	1.98	2.13	4.40	1562575	366	1364
Yield	0.92	2.35	3.84	2.94	4.60	1562575	366	1364

Notes: Summary statistics for the bond characteristics of the bonds included in the complete sample from January 2014 to April 2024.

Table A2: Bond market coverage

Year	Firms	Bonds	Average daily volume
2014	71	114	45 338 343 096
2015	97	164	72 787 643 409
2016	125	245	104 402 202 947
2017	164	340	158 889 104 123
2018	193	439	219 029 383 518
2019	245	615	295 310 037 217
2020	287	840	429 001 956 251
2021	330	1025	550 384 095 336
2022	343	1183	644 456 186 743
2023	358	1339	746 166 580 135
2024	353	1333	781 550 291 331

Notes: Coverage of firms and bonds over the complete sample period. Due to the limited data availability in the early years, all relevant bond market results are confirmed for the sub-period starting in 2022.

Further details on the bond selection and aggregation

- restrict the sample to issuance volumes above 1 million euros
- restrict the sample to senior-unsecured bonds
- remove bonds with less than 100 days of data
- remove bonds with yields above 100 percent
- keep bonds for which PD measures are available
- remove bonds with a negative spread
- remove stale priced bonds for which price remains unchanged over 20 days
- compute spreads by matching corporate bond yields with interest rates on German federal securities estimated for maturities of 6 months, 1 year, 2 years, up to 30 years by the Bundesbank
- industry and country aggregation: Compute aggregates if at least three different firms have bonds outstanding on each day

Appendix A.2. Structural VAR and firm data

Table A3: Summary statistics - SVAR

	Mean	SD	P25	Median	P75
Spread	2.0798	0.36031	1.8094	2.024	2.2632
Default risk component	2.0958	0.17391	1.9569	2.0651	2.2107
EBP	-0.016046	0.24696	-0.1925	-0.051314	0.098335
Stoxx Europe 600	393.4004	46.8646	357.445	385.93	432.24
GPRD	116.435	53.2421	81.4733	106.857	140.8747
Gas TTF	33.7672	39.4071	15.38	19.99	28.4
VIXIE	41.3811	19.8446	29.6788	36.3907	46.9057

Notes: Summary statistics of the financial and news variables included in the SVAR estimation before the logarithmic transformation is applied to the Stoxx Europe 600, the GPRD, the Gas TTF, and the VIXIE series. Complete sample from January 2014 to April 2024.

Table A4: Summary statistics - Firm financials

	Mean	SD	P25	Median	P75	N
Investment	0.015566	0.27926	-0.01375	0.007088	0.035536	2911
PPE (net, bn)	14.28687	35.0587	2.151	5.628	13.78	2911
Total Assets (bn)	48.47657	91.5569	10.3922	22.13814	50.0625	2911
Leverage	0.97544	23.68403	0.579405	0.995434	1.467415	2911
EBIT (mn)	702.034	1764.653	110.859	297.386	797.500	2880
Interest expense (mn)	-142.527	380.507	-114.371	-48.728	-23.180	2856
Spread	2.108984	4.386772	1.033244	1.378178	2.051838	2911

Notes: Summary statistics of the financial variables of bond issuing firms. Leverage is defined as total debt over total equity, investment as the log-difference in net property plant and equipment (PPE), and the spread is calculated as the unweighted average spread over all outstanding bonds per firm and quarter. Quarterly data between 2014 Q1 and 2024 Q1.

Table A5: Firms with high Russia exposure

	Firms
High RU risk:	ASML HOLDING NV, BAYWA AG, CARLSBERG BREWERIES A/S, EIFFAGE SA, ELECTROLUX AB, ENEL SPA, ERAMET SA, FERROVIAL SE, FRAPORT FRANKFURT AIRPORT SERVICES, FRESENIUS SE & CO KGAA, HELLA GMBH & CO KGAA, HOCHTIEF AG, IMERYS SA, KEMIRA OYJ, METRO AG, NOKIA CORP, NOKIAN TYRES PLC, NV BEKAERT SA, PROSUS NV, QUADIENT SA, RENAULT SA, RWE AG, SACYR SA, SNAM SPA, SPIE SA, STORA ENSO OYJ, TERNA RETE ELETTRICA NAZIONALE SPA, UBISOFT ENTERTAINMENT SA, VEOLIA ENVIRONNEMENT SA, VINCI SA, VIVENDI SE, VOESTALPINE AG, WEBUILD SPA, YIT OYJ

Notes: This table lists firms classified as having a high Russia dependence, measured by the earnings call index of Hassan et al. (2024). Firms are classified as having a high Russia exposure if their Russia-specific risk index is above the 80th percentile on average in the years 2019 and 2020 (the last two available years before the full-scale invasion of Ukraine).

Appendix A.3. Short-term business statistics

Table A6: Overview variables - Business statistics and country controls

Variable	Definition	Period	Source	Level
Bankruptcy	Total number of legal units filed for bankruptcy - Index	2015M1 - 2023M12	Eurostat - STBS	country-sector
Bankruptcy (quarterly)	Total number of legal units filed for bankruptcy - Index	2015M1 - 2023M12	Eurostat - STBS	country-sector
Import prices	Price of imported goods purchased from non-domestic areas in industry - Index	2014M1 - 2023M12	Eurostat - STBS	country-product
CPI	Consumer Price Index - Index	2014M1 - 2023M12	IMF - IFS	country
FX	Nominal effective exchange rate - Index	2014M1 - 2023M12	IMF - IFS	country
IP	Industrial Production - Index	2014M1 - 2023M12	IMF - IFS	country
10-y yield	Yield on 10-year government bonds	2014M1 - 2023M12	Datastream	country

Notes: Overview of the definition, coverage, and source of the variables included in the local projection estimations.

Table A7: Summary statistics - Business statistics and country controls

variable	Mean	SD	P25	Median	P75	N	Countries
Bankruptcy	151.3267	87.06697	96.5	135.5	188.3	5913	9
Bankruptcy (qtr)	128.6294	69.15154	81.8	116.7	160.6	3249	18
Import prices	99.42449	12.35502	93.7	98.1	103.1	18224	12
Δ IP	0.119247	11.66531	-5.9196	0.618466	7.170016	18224	12
Δ 10-y yield	0.001064	0.249204	-0.115	-0.02	0.1	18206	12
Δ CPI	0.202196	0.729042	-0.13113	0.160037	0.513161	18224	12
Δ FX	0.030712	0.745552	-0.35818	-0.00876	0.446119	18224	12

Notes: Summary statistics of the business statistics and country controls included in the local projection estimations.

Appendix B. Additional information - sanction shock identification

Appendix B.1. Background and timeline of EU-Russia restrictive measures

The EU imposed its first sanctions against Russia in response to the Russian annexation of Crimea in early 2014. These sanctions included travel bans and asset freezes of individuals involved in the Russian military operation. As Russia further escalated the situation through its military presence in the Ukrainian Eastern provinces of Donetsk and Luhansk, the US imposed sectoral sanctions, which according to the White House were "by far the most comprehensive sanctions applied to Russia since the end of the Cold War" [1]. Initially, the EU refrained from comparable measures. Only after the shooting down of flight MH17 by pro-separatist forces supported by Russia in July 2014, EU leaders decided to impose broader sectoral sanctions. The EU followed the US in implementing financial sanctions, imposed an arms embargo, and banned the export of dual-use products. No sanctions were imposed on the energy sector at the time by the EU. Russia responded to western sanctions with an import stop for agricultural products from countries imposing sanctions on Russia in an effort to limit its western dependence. Contrary to what would later unfold during the full-scale invasion of Ukraine in 2022, Russia was not able to profit from rising energy prices after the annexation of Crimea in 2014. Falling oil prices, as the OPEC attempted to outprice US shale production, further weighed on Russian state finances. The US sanctions on the energy sector made a bailout of Russia's largest oil company Rosneft through the Russian central bank necessary. This bailout led to a 30% collapse of the ruble in a single day with major repercussions for the Russian economy. The economic impact for the EU of sanctions imposed against Russia in 2014 and the beginning of 2015 was mild, given that crucial links, in particular in the energy sector, were not touched and Russian countersanctions were only weakly enforced. While sanctions were extended and tightened over the years 2015 to 2018, significant new measures were only taken after the attempted assassination of former agent Sergei Skripal and his daughter on British soil followed by an expulsion of diplomats on both sides.

On February 23, 2022, the day before the Russian full-scale invasion of Ukraine, the EU imposed the first sanction package as a response to the Russian decision "to proceed with the recognition of the non-government controlled areas of Donetsk and Luhansk oblasts in Ukraine as independent entities, and the ensuing decision to send Russian troops into these areas" [2]. Over the following two years, another 12

[1] The White House Press Office

[2] European Council

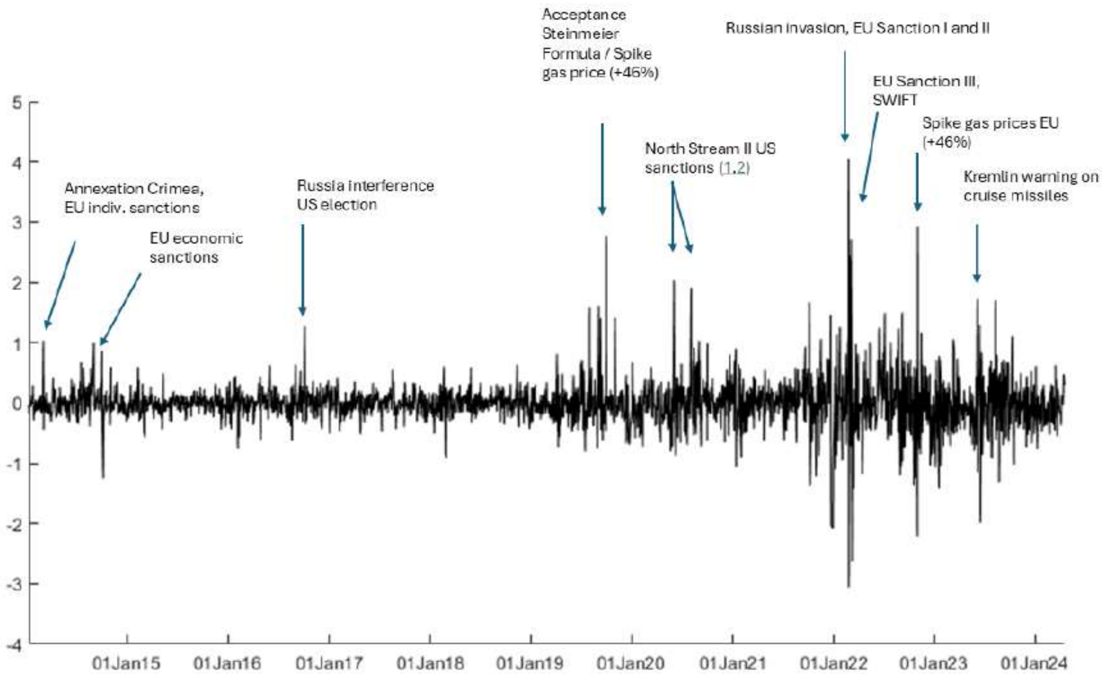
sanction packages would be announced by the EU. This time, far-reaching financial and economic measures were taken, including a ban of 10 Russian banks from the international payment system SWIFT as well as an import ban on the energy sector. The imposed sanctions include six main areas: Energy, Finance, Transport, Trade, Services, and Defense and Technology. Import restrictions among others include oil and coal, materials such as iron and steel, wood, paper and aluminium, as well as gold, diamonds, spirits, and seafood. Export restrictions were imposed on electronic components, chemicals, luxury goods including vehicles, and machinery components. In total, 54% of pre-war exports from the EU and 58% of pre-war imports in the EU from Russia fall under these measures [3]. While no EU sanctions were imposed on gas imports, the stop of pipeline gas imports through Northstream 1 and 2 and the Yamal pipeline meant a substantial drop in total gas imports from Russia. Germany in particular, having been the main importer of Russian gas before the war, stopped importing gas directly from Russia. Russia responded to Western sanctions with FX restrictions for foreign banks, restrictions on dividend payments to foreigners, and export restrictions of selected goods among others. A full timeline of these and other measures taken by both parties is given in Online Appendix B, Table A8.

[3] European Commission

Table A8: List of announcement days of restrictive measures by the EU and Russia

Date	Event	Announcement by
06.03.2014	Extraordinary meeting EU heads of state; Start preparation individual sanctions	EU
17.03.2014	Introduction of a first set of restrictive measures against 21 Russian and Ukrainian officials	EU
20.03.2014	EU leader request preparation of broader economic sanctions; futher names added to individual sanctions	EU
12.05.2014	Agreement on new set of sanctions	EU
23.06.2014	Import ban on goods from Crimea	EU
16.07.2014	Meeting European Council: 6 additional restrictive measures against Russia	EU
18.07.2014	Ukraine crisis: EU broadens remit of sanctions	EU
22.07.2014	Council demands sanctions in four sectors after downing of MH17	EU
25.07.2014	Further EU sanctions over situation in Eastern Ukraine	EU
29.07.2014	Adoption of economic sanctions against Russia	EU
06.08.2014	Russia bans the import of foodstuffs from sanctioning countries	RU
07.08.2014	Russia defines list of sanctioned products and countries	RU
30.08.2014	European Council asks for preparation of new economic sanctions	EU
12.09.2014	Further economic sanctions on Russia	EU
17.11.2014	EU ministers aks for proposal on further economic sanctions	EU
28.11.2014	EU strengthens sanctions against separatists in Eastern Ukraine	EU
12.02.2015	Minsk II	EU/RU
16.02.2015	EU strengthens sanctions against separatists in Eastern Ukraine	EU
30.03.2018	Russia orders diplomats out (Skripal)	RU
23.02.2022	First package of sanctions against Russia	EU
24.02.2022	Russian full-scale invasion of Ukraine starts; EU leaders agree on further sanctions	EU/RU
25.02.2022	Second package of sanctions in response to Russia's invasion of Ukraine	EU
28.02.2022	Third package of sanctions in response to Russia's invasion of Ukraine / FX restrictions to balance ruble (Decree 79) / Ban EU air carriers	EU/RU
01.03.2022	Restrictions cash withdrawal (Decree 81)	RU
02.03.2022	SWIFT ban Russian banks	EU
04.03.2022	Profit payments to foreigners (Decree 254), Sanctions on individuals (Decree 30-FZ)	RU
06.03.2022	Procedure permits for transactions (Decree 295)	RU
08.03.2022	Export ban (Decree 100, Government order 311)	RU
14.03.2022	Ban on transactions of RU insurance corporations with foreign (Law 55-FZ)	RU
15.03.2022	Fourth package of sanctions in response to Russia's invasion of Ukraine	EU
18.03.2022	Additional restrictions of FX and transactions (Decree 126)	RU
31.03.2022	Payment gas in rubles (Decree 172)	RU
01.04.2022	Foreign banks not allowed to buy other currencies in Russia (Decision "On Establishment of the Amount of Certain Transactions of Residents and Non-residents")	RU
08.04.2022	Fifth package of sanctions in response to Russia's invasion of Ukraine	EU
16.04.2022	Ban on issuance and trade of depositary receipts outside Russia (114-FZ)	RU
03.05.2022	Trade with sanctioned individuals (Decree 252)	RU
27.05.2022	Payments for IP via special accounts (Decree 322)	RU
31.05.2022	European Council agrees on sixth sanctions package	EU
06.10.2022	Eighth package of sanctions in response to Russia's invasion of Ukraine	EU
16.12.2022	Ninth package of sanctions in response to Russia's invasion of Ukraine	EU
25.02.2023	Tenth package of sanctions in response to Russia's invasion of Ukraine	EU
23.06.2023	Eleventh package of sanctions in response to Russia's invasion of Ukraine	EU
18.12.2023	Twelfth package of sanctions in response to Russia's invasion of Ukraine	EU
23.02.2024	EU adopts 13th package of sanctions against Russia	EU

Figure A1: Shock series and major conflict events



Notes: Daily sanction shock series extracted from the structural VAR including credit spreads, and the logarithmic transformation of the Stoxx Europe, the GPRD, the Gas TTF, and the VIXIE. Individual spikes are connected to conlfict events.

Appendix B.2. The pivotal role of gas prices for sanction shock identification

The previous analysis highlighted the importance of gas prices as a highly responsive series to EU-Russia conflict for the identification of the sanction shock. The pivotal role of gas prices in the identification approach is also reflected in the estimates of the variance-covariance matrices of the VAR reduced form errors under the two regimes. Both the variance and the covariances between gas prices and the other financial and news variables in the model change strongly between announcement and non-announcement days, with substantially stronger co-movement on announcement days (Tables A9 and A10).

Table A9: Estimate variance-covariance matrix of reduced form errors - non-announcement days

$\hat{\Sigma}_0$	Spread	Estoxx	GPRD	VIXIE	TTF Gas
Spread	0.028	-0.002	-0.001	0.004	0.000
Estoxx		0.008	0.003	-0.010	0.000
GPRD			0.651	-0.005	0.001
VIXIE				0.026	0.000
TTF Gas					0.003

Table A10: Estimate variance-covariance matrix of reduced form errors - announcement days

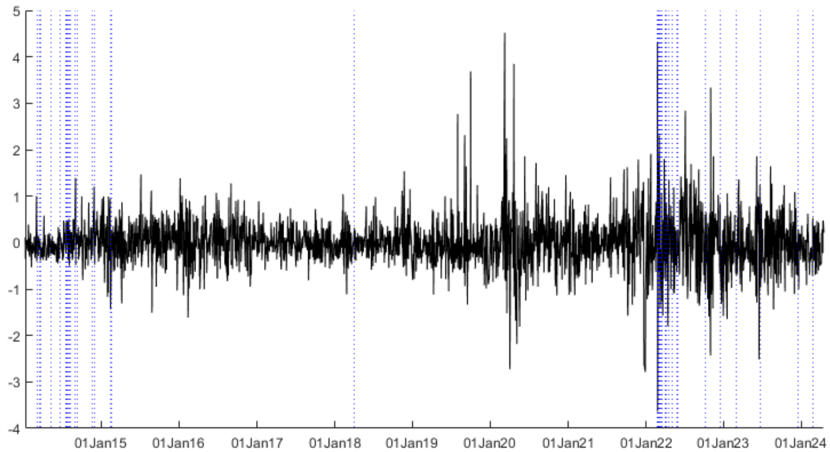
$\hat{\Sigma}_1$	Spread	Estoxx	GPRD	VIXIE	TTF Gas
Spread	0.029	-0.003	-0.004	0.005	0.011
Estoxx		0.010	0.004	-0.015	-0.011
GPRD			0.655	0.002	0.035
VIXIE				0.042	0.020
TTF Gas					0.030

Notes: The variance-covariance matrices are calculated as $\hat{\Sigma}_i = \frac{1}{\#T_i}\sum_{t\in T_i} \hat{u}_i\hat{u}_i{}'$ for sub-samples $i = 0, 1$. The variance-covariances are estimated over the complete sample of daily data between January 2014 and April 2024.

One potential concern regarding the identification of the sanction shock is that factors, unrelated to the EU-Russia conflict, could impact the EU commodity prices on the selected event-days. To rule out this possibility, I linearly regress the TTF front-month gas prices on the Brent oil price (and a constant) to separate comovement in EU energy prices from the orthogonal gas price-specific component. Before the full-scale invasion, over 40% of the EU's gas imports and 25% of its oil imports came from Russia. Moreover, the EU relied heavily on its pipeline infrastructure for cheap access to natural gas from Russia. The orthogonal component of gas prices is, thus, expected to capture the conflict effects, beyond what is already reflected in oil prices.

I replace the gas price series in the structural VAR estimation by the gas price component orthogonal to oil prices and re-estimate the model under precisely the same assumptions as in the baseline specification. Again, we reject the assumption of equal variance-covariance matrices on announcement days and non-announcement days over the full sample period (p-value: 0.01). We again do not reject the null hypothesis of a single shock only on announcement days (p-value: 0.83). Also, the shock series resembles the series obtained in the baseline model specification.

Figure A2: Sanction shock series - Gas price component orthogonal to oil prices

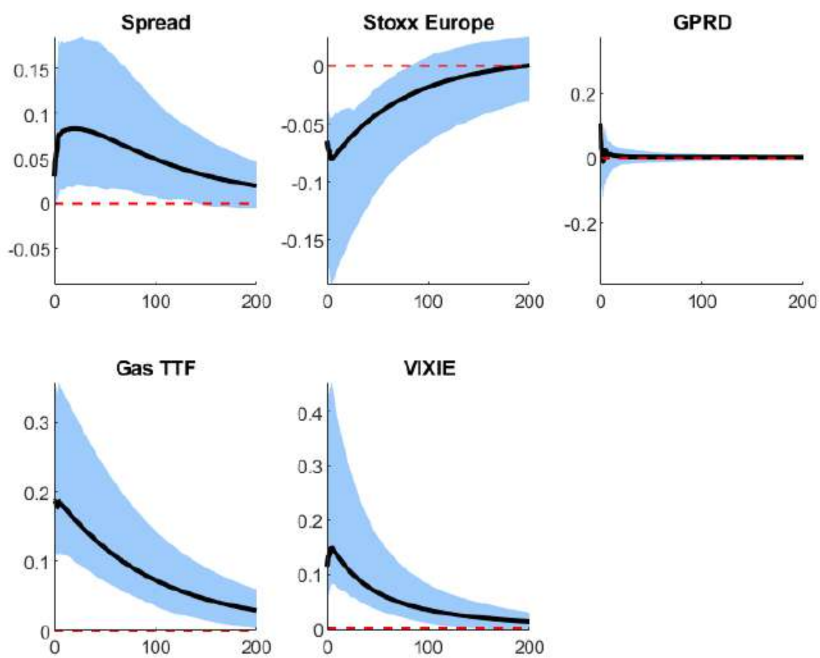


Notes: Daily sanction shock series extracted from the structural VAR including credit spreads, and the logarithmic transformation of the Stoxx Europe, the GPRD, the component of Gas TTF orthogonal to the Brent oil price, and the VIXIE. Dotted lines correspond to the 44 (counter)sanction announcement days selected to identify the shock.

Impulse response functions to a unitary sanction shock, as estimated in the model including the gas price component unrelated to oil price movements, confirm the findings of the baseline model specification. Even though the effect of the sanction shock in this setting is somewhat dampened, significant effects on the credit spreads are again found especially for the sample of intensified conflict starting in 2022 (Figures A3, A4).

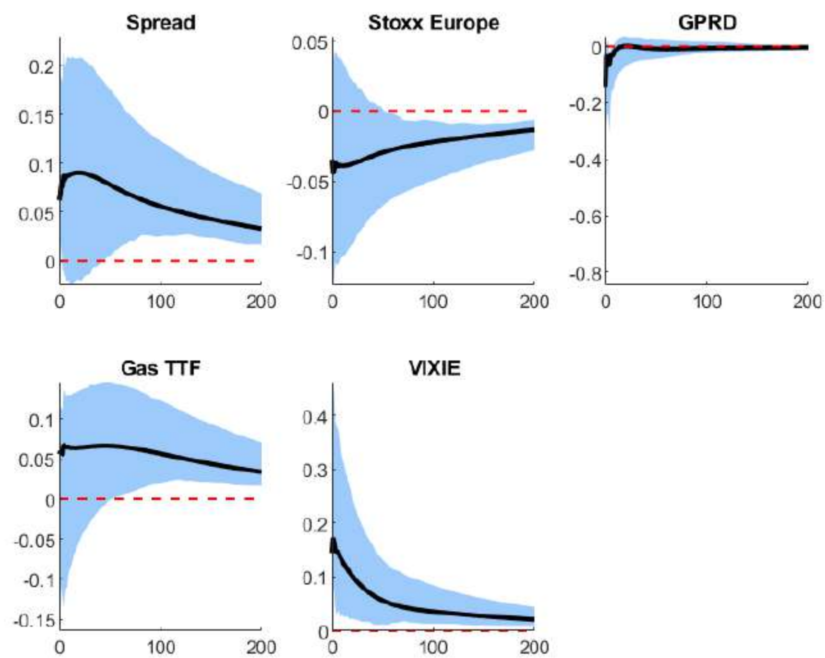
If we replace the EU gas price series by the CBOE Crude Oil Volatility Index, reflecting uncertainty in global oil prices, and re-estimate the structural VAR, the change in the variance covariance-matrix between announcement and non-announcement days is not sufficient to identify the shock (p-value: 0.68). This confirms that general energy uncertainty cannot explain the observed results.

Figure A3: Effect of a sanction shock on credit spreads 2014 to 2024 - Gas price component orthogonal to oil prices



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. Only the component of the Gas TTF orthogonal to Brent oil prices is included. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Figure A4: Effect of a sanction shock on credit spreads 2022 to 2024 - Gas price component orthogonal to oil prices



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. Only the component of the Gas TTF orthogonal to Brent oil prices is included. All variables are standardised to have a zero mean and a unit variance. Daily data between January 4, 2022 and April 15, 2024.

Appendix B.3. Robustness: Excluding days with economic events and data releases

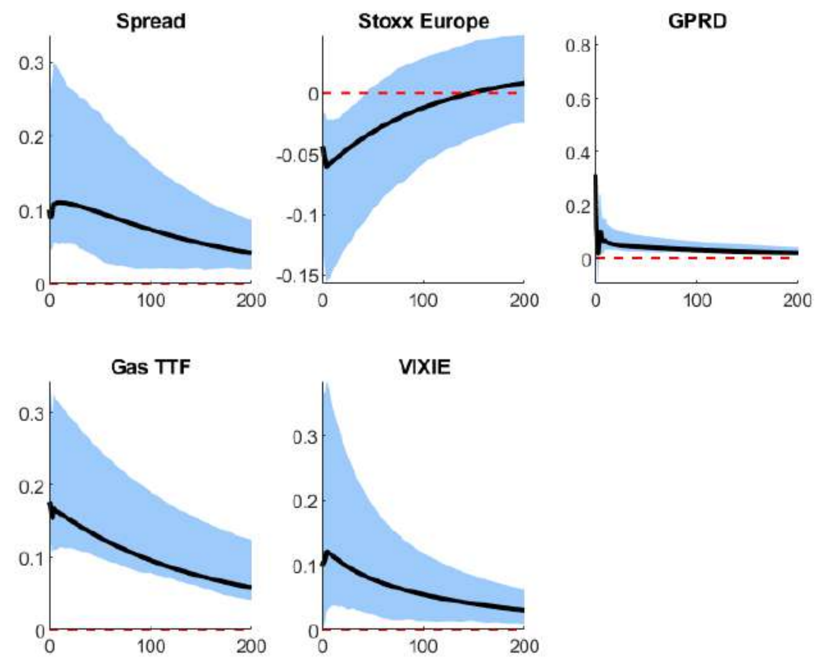
To exclude the possibility of other events contaminating the selected event days, I proceed as follows: In a first step, I collect economic events and data releases coinciding with sanction announcement days from the Bloomberg Eurozone calendar. Economic events coincide with sanction announcements on eight days, which I exclude in a robustness check. Results remain extremely robust (Figure A5). Data releases are substantially more frequent (releases happen on 32 of the 44 announcement days) such that overlapping days cannot simply be excluded. Therefore, for each announcement day with economic releases, I assess the relevance of the release using two different approaches. First, I use the Bloomberg relevance score and exclude event days for which a release with a relevance above 80 was made. Using this logic 12 announcement days are removed. Secondly, I construct a metric for the importance of the economic data release relative to the sanction announcement. I compare the number of articles on an overlapping day that contain the keywords of the corresponding release (e.g. "CPI", "PMI", "unemployment rate", etc. and one of "Eurozone", "euro area", "Europe", "EU") with the number of articles mentioning "sanctions", "Russia", and "Ukraine". This gives an indication of the relative signal strength the VAR picks up from the sanction intensity shock and from a possible other economic shock on such an announcement day. I exclude articles for which the share of release articles relative to sanction articles exceeds 0.25. This strategy removes 14 announcement days. Results are extremely robust to both approaches (Figures A6 and A7). Excluding days with a high relative importance of economic data releases even strengthens the effects somewhat. This confirms that the results are not driven by alternative macro events and indeed capture effects of a sanction intensity shock.

Table A11: Test identification assumptions (p-values)

Sample	H0: $\Sigma_1 = \Sigma_0$	H0: $\Sigma_1 - \Sigma_0 = b_1 b_1'$
Excluding events	0.000	0.846
Excluding releases relative	0.000	0.854
Excluding releases absolute	0.000	0.880

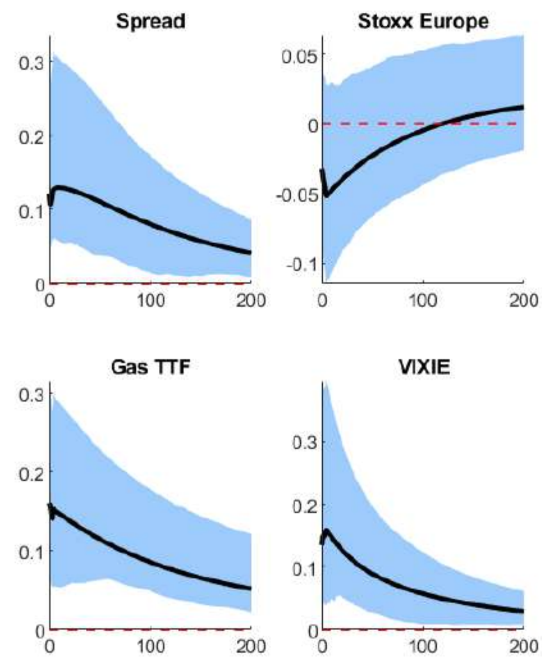
Notes: P-values derived from the bootstrapped distribution of the Wald test statistics given in Equation 12 (left column) and Equation 10 (right column). All observations are used in all samples to compute the variance-covariance matrices. A moving-block bootstrap of Jentsch and Lunsford (2019) is performed with 1000 repetitions. Following the authors, the block length is set at $l = 5 * T^{\frac{1}{4}}$ for each sample. Additional information on the implementation of the bootstrap is given by Boer et al. (2023).

Figure A5: Effect of a sanction shock on credit spreads, 2014 to 2024, excluding economic events



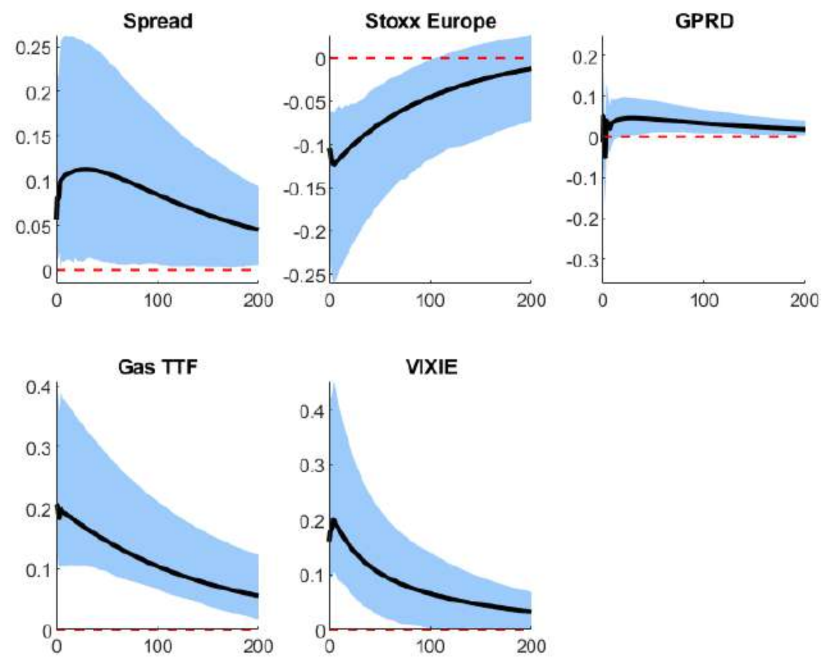
Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. Sanction announcement days coinciding with economic events are excluded. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Figure A6: Effect of a sanction shock on credit spreads, 2014 to 2024, excluding economic release days (relative)



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. Sanction announcement days on which newspaper coverage of economic data releases exceed 0.25 the coverage of sanctions are excluded. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Figure A7: Effect of a sanction shock on credit spreads, 2014 to 2024, excluding economic release days (absolute)



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. Sanction announcement days on which economic data releases with a Bloomberg relevance score above 80 are excluded. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Appendix B.4. An alternative model with multiple shocks

The assumption of a single sanction intensity shock on announcement days can be relaxed to a setting in which all shocks in the model are allowed to change variance between announcement days and non-announcement days. In this setting, the restrictiveness of the identification assumptions can be evaluated. The covariance matrices on announcement days (Σ_0) and non-announcement days (Σ_1) can be decomposed into

$$\Sigma_0 = BB' \; and \; \Sigma_1 = B\Lambda B' \tag{B.1}$$

where $Lambda = diag(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5)$ contains the structural shock variances on announcement days and B the constant impact coefficients. As before, structural shock variances on non-announcement days are normalised to one. We can rewrite $\Sigma_1\Sigma_0^{-1} = B\Lambda B' \, (BB')^{-1} = B\Lambda(B')^{-1}$, giving the eigendecomposition of the matrix $\Sigma_1\Sigma_0^{-1}$. Estimating this matrix, the coefficient vectors $\hat{b}_i$ and the variance shifters $\hat{\lambda}_i$ for $i = 1, ..., 5$ are obtained as the eigenvectors and eigenvalues, respectively (Lütkepohl et al. (2021), Boer et al. (2023)). The resulting variance shifts are reported in Table A12 for the full sample period and in Table A13 for the sub-period starting in 2022. These shifts let us investigate the two main assumptions in the partially identified model: 1) The presence of a shift in variance in the first shock and 2) no other shifts in the variances of the other shocks. The results provide clear evidence of a unique shock on sanction announcement days. The shock estimate for the first shock is with $\hat{\lambda}_1 = 9.704$ for the complete sample period and with $\hat{\lambda}_1 = 6.353$ for the post-2022 period, significantly larger than one on a 5% significance level. All other shocks in the model do not experience an increase in their variance on announcement days relative to non-announcement days at this significance level. For the post-2022 period, we see, while statistically insignificant, some increase in the variances of the second, third, and fourth shock. Figure A8 shows the impulse response function of the dominating shock in this unrestricted model. We observe very similar dynamics as for the restricted model. This suggests that even if we don't rule out the possibility of other shocks changing on announcement days after 2022, the dominant shock behaves like the sanction intensity shock over the full sample period. These additional results confirm that the results in the paper are not driven by inappropriate assumptions and confirm the applicability of the restricted model used in the main part of the paper.

Table A12: Relative variances on sanction announcement days

	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	$\hat{\lambda}_5$
2.5%	1.284	0.750	0.483	0.295	0.137
5%	1.456	0.820	0.544	0.336	0.173
16%	2.063	1.005	0.658	0.433	0.255
Estimate	9.704	1.367	1.064	0.915	0.481
84%	14.273	1.840	1.306	0.961	0.531
95%	17.658	2.247	1.491	1.110	0.610
97.5%	18.808	2.450	1.597	1.179	0.650

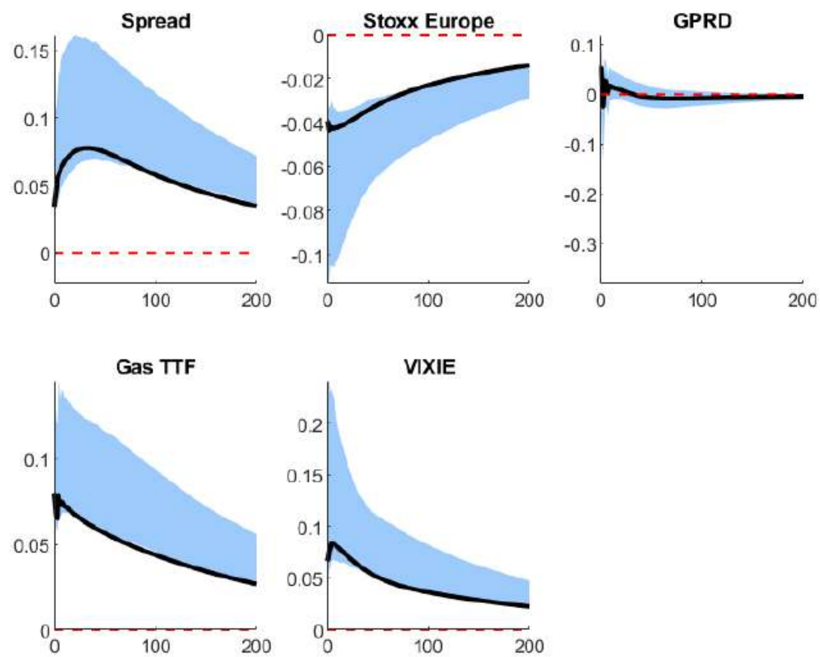
Notes: 68%, 90%, and 95% confidence intervals obtained from a moving-block bootstrap with 1000 repetitions. Full sample from 2014 to 2024.

Table A13: Relative variances on sanction announcement days

	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	$\hat{\lambda}_5$
2.5%	1.531	0.867	0.400	0.154	0.021
5%	1.763	1.017	0.480	0.225	0.148
16%	2.541	1.399	0.743	0.381	0.148
Estimate	6.353	1.827	1.604	1.348	0.580
84%	8.347	2.492	1.847	1.287	0.590
95%	10.055	3.109	2.115	1.591	0.701
97.5%	11.458	3.486	2.253	1.708	0.754

Notes: 68%, 90%, and 95% confidence intervals obtained from a moving-block bootstrap with 1000 repetitions. Sub-sample from 2022 to 2024.

Figure A8: Effect of a sanction shock on credit spreads 2022 to 2024 - Fully identified model



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. Only the component of the Gas TTF orthogonal to Brent oil prices is included. All variables are standardised to have a zero mean and a unit variance. Daily data between January 1, 2022 and April 15, 2024.

Appendix B.5. Alternative shock identification approach: Proxy-VAR

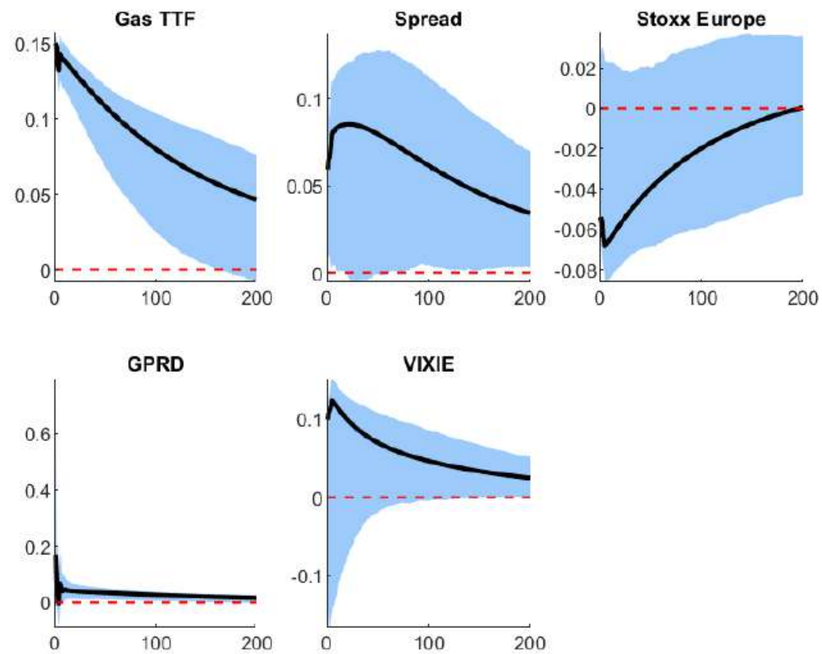
The shock identification presented in the main part of the paper follows a statistical approach exploiting variance changes to deduce shock intensity, with the caveat that assumptions on the structure of the variance changes are needed. An alternative approach, which also exploits the responsiveness of gas prices to sanction announcements, is a Proxy-VAR. This approach does not rely on assumptions regarding the structure of shock variances, instead it assumes exogeneity and relevance of the instrument:

$$E[z_t \epsilon_{1,t}] = \alpha \neq 0 \tag{B.2}$$

$$E[z_t \epsilon_{2:n,t}] = 0 \tag{B.3}$$

I follow the methodological approach of Stock and Watson (2012) and Mertens and Ravn (2013) and use an external proxy, in this case the sanction announcements, to identify sanction intensity in the VAR. Specifically, to increase instrument strength, I consider the change in gas prices on the announcement days. Assuming that gas price changes on announcement days capture sanction intensity and that no other shocks lead to price movements on such days, the resulting dynamics give the effect of a sanction intensity shock purely identified using gas prices on corporate credit spreads. I verify that Alessandri and Gazzani (2025) do not identify gas supply shocks that are not sanction-related on announcement days. When regressing the gas price residuals on the instrument, we obtain an extremely high F-statistic of 391. This is unsurprising as the instrument matches the exact magnitude of the gas price change and as price movements on announcement days are large. Again, I apply the moving-block bootstrap of Jentsch and Lunsford (2019) for asymptotically correct inference. At the core of this approach lies the assumption that the shock of interest, the sanction intensity shock, is correlated with gas price changes on announcement days but that all other shocks in the model are uncorrelated with such announcements. This approach does not rely on changes in the shock variance as assumed in the main part of the paper. A sanction intensity shock, normalised to increase gas prices by 0.15 standard deviations as in the baseline model, leads to an increase in the spread of close to 0.1 standard deviations or 4 basis points (Figure A9). This is exactly the magnitude as the sanction intensity shock identified by heteroskedasticity. Similarly, the effect on the stock market, on geopolitical risk, and on bond market volatility are very similar to the baseline model. These results confirm the core finding of the paper without relying on assumptions regarding the structure of the shock variances, underlining the robustness of the results.

Figure A9: Effect of a sanction intensity shock on credit spreads, 2014 to 2024, Proxy VAR with gas price changes on sanction days

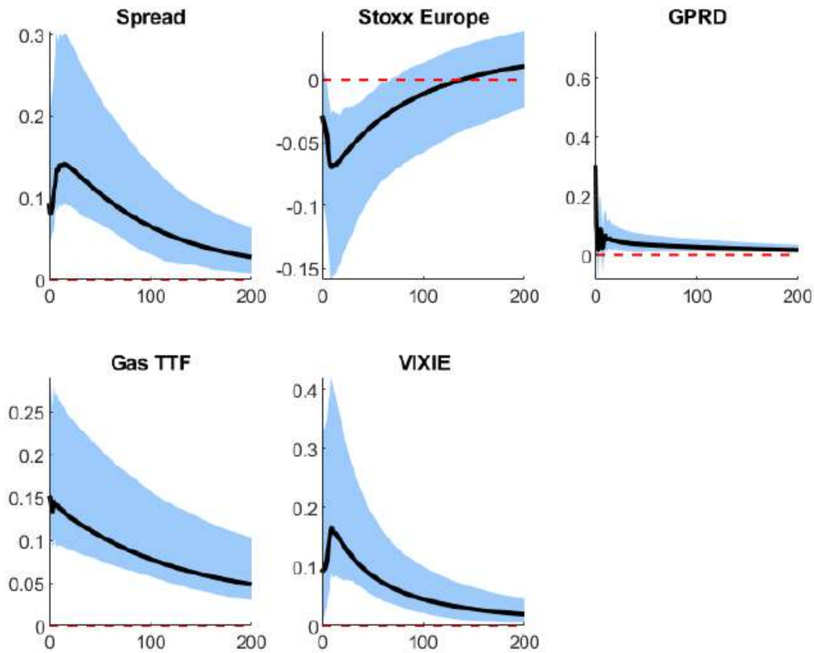


Notes: Impulse response function to an adverse sanction intensity shock together with the 90% bootstrapped confidence interval over a 200-day horizon. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Appendix B.6. Robustness lag length and placebo tests

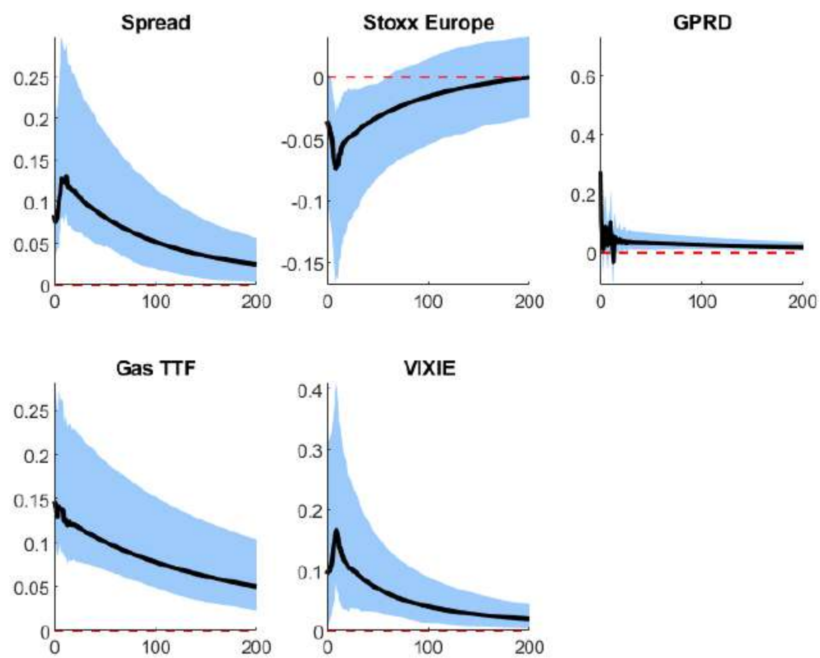
To ensure that the core result is robust to the inclusion of a higher-order of lags, I re-estimate the model with 10-day and 15-day lag lengths. Both specifications confirm the results of the baseline model. Moreover, I ensure that the results are indeed a manifestation of the selected announcement days, rather than a general feature of the chosen approach. For this purpose, I perform two placebo tests. In a first test, I randomly allocate the 44 events over the complete sample period from 2014 to 2024. In a second test, to further ensure that the results are not merely a representation of a higher frequency of events after the start of the full-scale invasion of Ukraine, I randomly scatter the same number of events separately over the pre-2022 period (19 events) and the post 2022 period (25 events) ensuring that they do not fall on actual announcement days. For each approach, I calculate the distribution of placebo responses by iteratively performing this exercise 500 times. I then validate that the original responses, obtained using the actual event days, fall outside the distribution obtained by randomly scattering events over the complete period or the sub-periods. The results, with responses for the spread, the GPR, gas prices, and bond market volatility falling outside the distribution of placebo responses, confirm that the documented effects are specific to sanction announcements and not a general feature of the data, the model, and the identification approach. The placebo distributions are centered around zero for all variables. By construction, the placebo distribution for gas prices does not contain zero on impact. For each draw, the shock is identified up to a sign only, where the sign is set to have a positive effect on gas prices. These exercises provide further validation of the selected approach.

Figure A10: Effect of a sanction shock on credit spreads, 2014 to 2024, 10-day lag



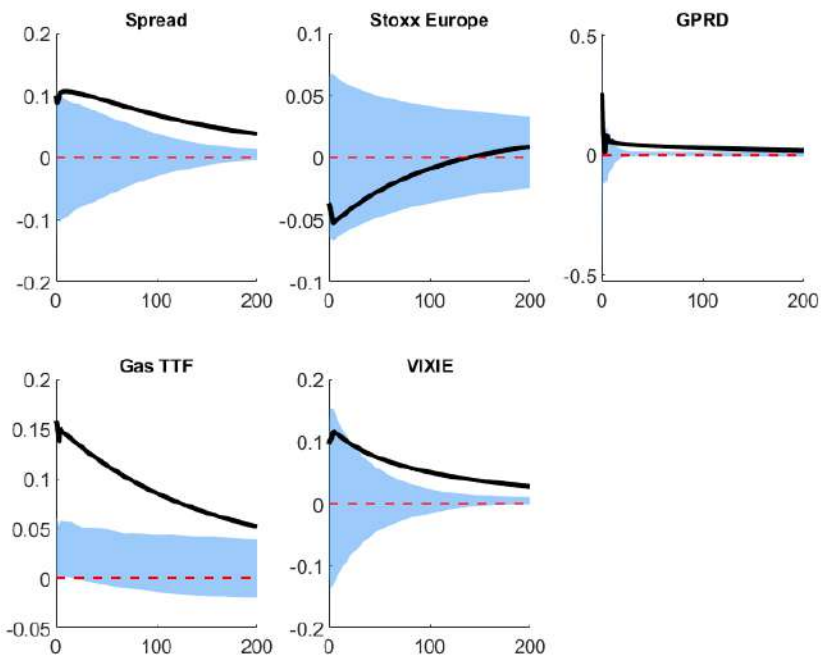
Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Figure A11: Effect of a sanction shock on credit spreads, 2014 to 2024, 15-day lag



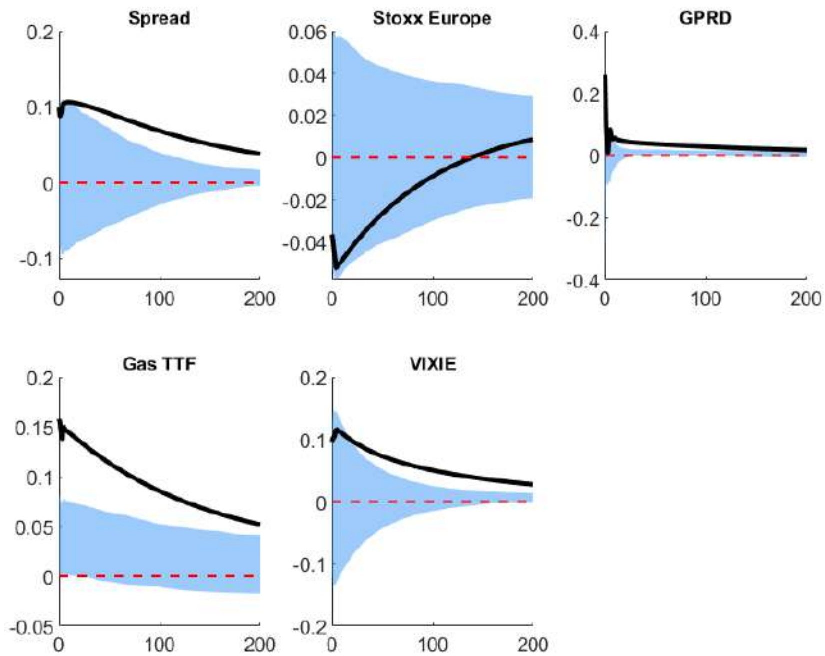
Notes: Impulse response function to a unitary adverse sanction shock together with the 90% bootstrapped standard errors over a 200-day horizon. A logarithmic transformation is applied to the Stoxx Europe, GPRD, Gas TTF, and VIXIE. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Figure A12: Effect of a sanction shock together with the placebo distribution (events randomly scattered over full sample period)



Notes: Impulse response function to a unitary adverse sanction shock together with the 90% response sample obtained from randomly scattering events over the complete sample period. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Figure A13: Effect of a sanction shock together with the placebo distribution (events proportionally scattered over the pre-2022 and post-2022 periods)



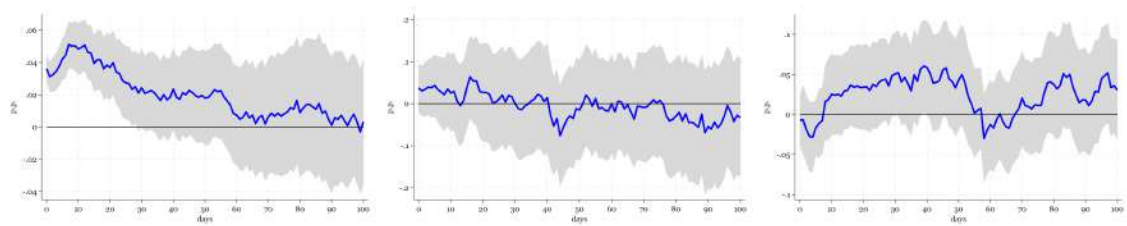
Notes: Impulse response function to a unitary adverse sanction shock together with the 90% response sample obtained from randomly scattering events over the pre-2022 and post-2022 sample periods in line with the actual count of announcements over the two sub-samples. All variables are standardised to have a zero mean and a unit variance. Daily data between January 2, 2014 and April 15, 2024.

Appendix B.7. Placebo exercise for Hungary and Slovakia

Not all member countries participated similarly in the EU's sanction regime. EU processes allowed some countries to negotiate exemptions from core sanctions and to continue importing energy from Russia. In particular, Hungary and Slovakia, blocking EU sanction measures, negotiated exemptions for oil imports and are with an import share of 80%-85% still highly dependent on Russian gas[4] (EU average 2025[5]: 13%). We would, therefore, expect credit spreads to be less sensitive to EU-Russia sanction intensity for firms located in these countries. I estimate the model of Equation 13 for the baseline sample, as well as for the spread indices for Hungary and Slovakia separately. Bond spreads for euro-denominated bonds in Hungary and Slovakia are collected from Bloomberg. The sample includes 44 euro-denominated bonds issued by Slovakian firms and 11 by Hungarian firms. Interestingly, no significant effect of the sanction intensity shock is found for either Hungary or Slovakia on impact or after. These countries, while being similarly or even stronger exposed to the war in other respects such as geographic distance, were shielded from sanction pressures by exemptions. This exercise again confirms that the shock indeed captures sanction intensity during the EU-Russia conflict specifically, rather than merely capturing geopolitical risk more broadly.

Figure A14: Effect of a sanction shock on the excess bond premium and the default risk component

(a) Baseline (b) Hungary (c) Slovakia



Notes: Response of the credit spreads to a unitary sanction intensity shock together with the 90% confidence intervals. Controls include the logarithmically transformed Stoxx Europe, GPRD, Gas TTF, and VIXIE. Daily data between January 2, 2014 and April 15, 2024.

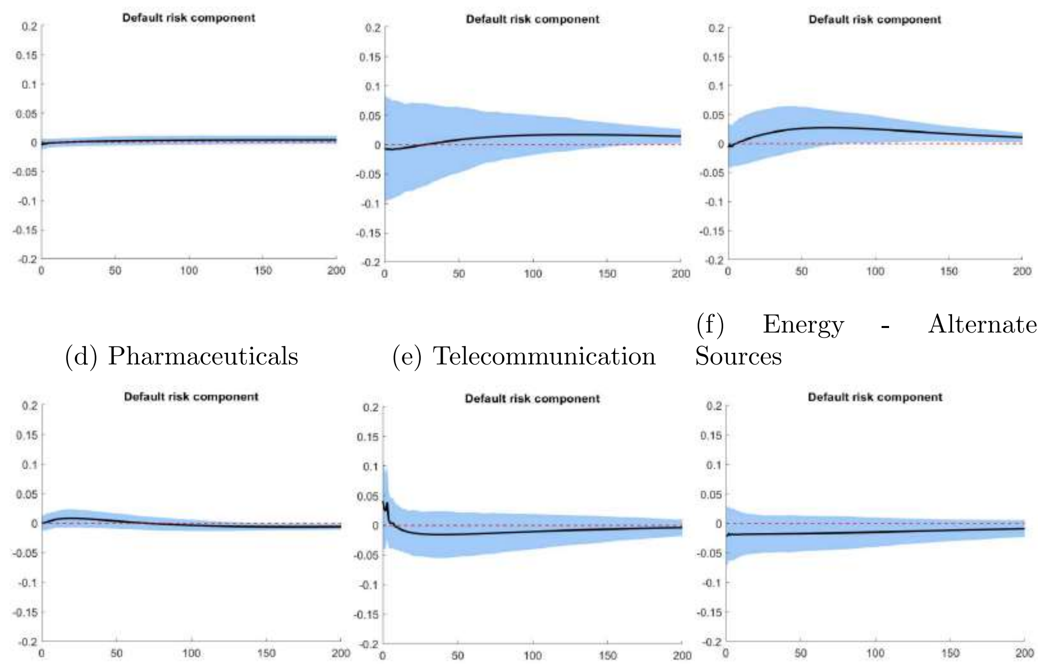
[4] Fitch

[5] EU

Appendix C. Additional results

Appendix C.1. Additional results - credit market and firm data

Figure A15: Selected industries less affected by sanction shocks



(a) Construction (b) Healthcare Products (c) Healthcare Services

(d) Pharmaceuticals (e) Telecommunication (f) Energy - Alternate Sources

Notes: Impulse response function to an adverse sanction shock together with the 90% bootstrapped standard errors. All variables are standardised to have a zero mean and a unit variance. Only industries for which at least three different firms have bonds outstanding at each point in time are depicted.

Table A14: Firm financial space and conflict impact (within-firm changes)

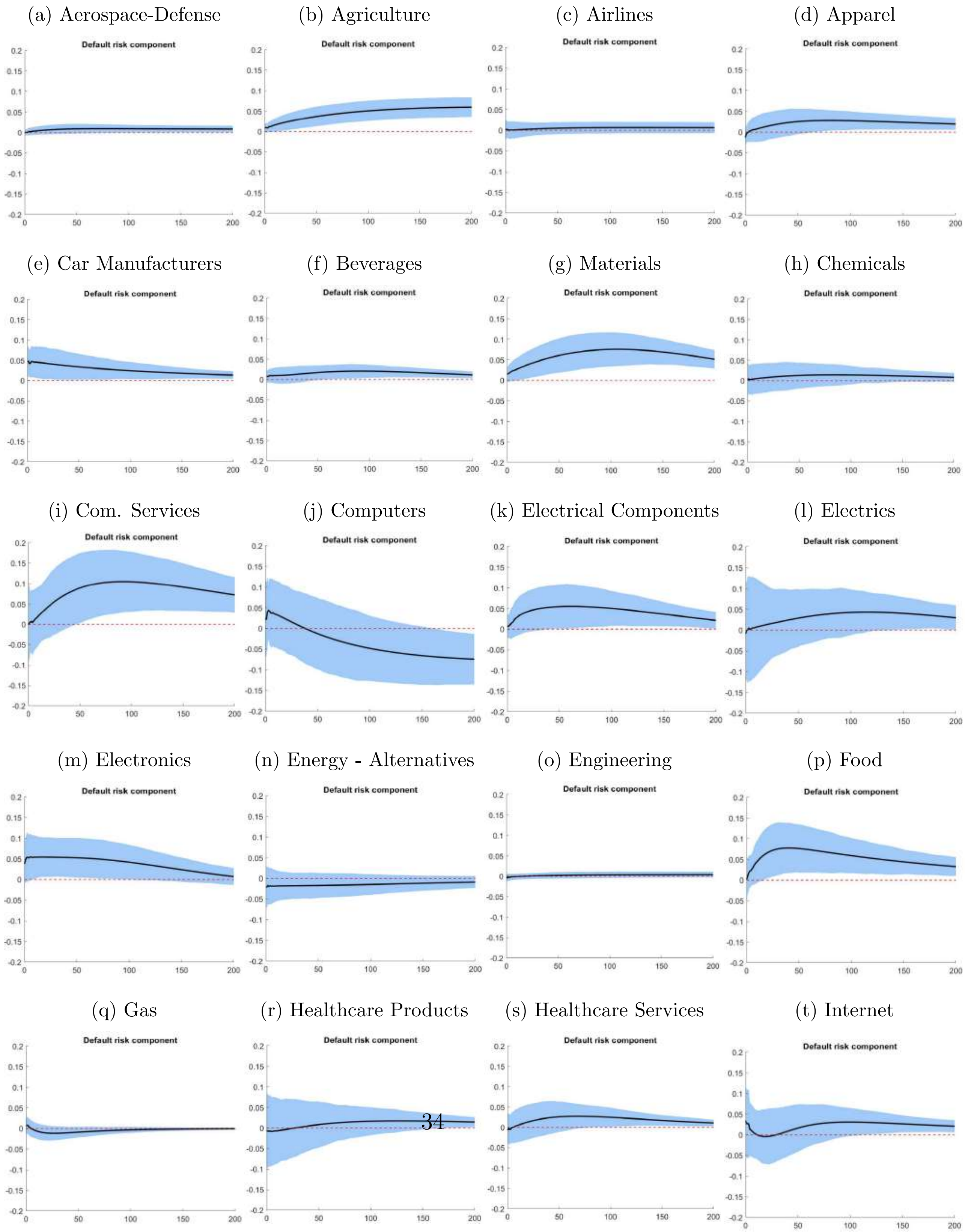
	(1) Spread	(2) EBP	(3) Default risk	(4) Spread	(5) EBP	(6) Default risk
L.sanction_shock	0.008	0.020^{**}	-0.012	0.043^{***}	0.039^{***}	0.004
	(0.016)	(0.008)	(0.010)	(0.016)	(0.007)	(0.012)
Low leverage	0.109	0.001	0.108			
	(0.230)	(0.086)	(0.214)			
High leverage	0.127	-0.030	0.157			
	(0.209)	(0.069)	(0.192)			
Low leverage*L.sanction_shock	0.012	-0.000	0.013			
	(0.019)	(0.011)	(0.011)			
High leverage*L.sanction_shock	0.080^{**}	0.038^{***}	0.042^{*}			
	(0.036)	(0.013)	(0.025)			
Low EBIT				0.045	0.022	0.024
				(0.086)	(0.073)	(0.050)
High EBIT				-0.075^{*}	-0.036	-0.039
				(0.039)	(0.024)	(0.026)
Low EBIT*L.sanction_shock				-0.001	-0.010	0.009
				(0.013)	(0.010)	(0.013)
High EBIT*L.sanction_shock				-0.013	-0.012	-0.002
N	663749	663749	663749	663749	663749	663749
Firms	189	189	189	189	189	189
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table examines the importance of collateral- and earnings-based borrowing constraints in a panel regress setting covering the period from January 2014 to April 2024. The dependent variables are the credit spread and its components, the excess bond premium (EBP) and the default risk component. Firms are dynamically grouped into equally sized bins according to their leverage and earnings levels. The intermediate bin is taken as a baseline. Stan errors are clustered at the firm level.

Figure A16: Industries - Part 1



(a) Aerospace-Defense (b) Agriculture (c) Airlines (d) Apparel

(e) Car Manufacturers (f) Beverages (g) Materials (h) Chemicals

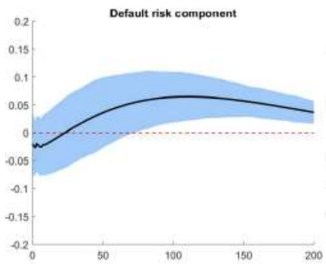
(i) Com. Services (j) Computers (k) Electrical Components (l) Electrics

(m) Electronics (n) Energy - Alternatives (o) Engineering (p) Food

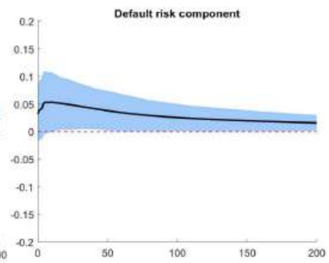
(q) Gas (r) Healthcare Products (s) Healthcare Services (t) Internet

Figure A17: Industries - Part 2

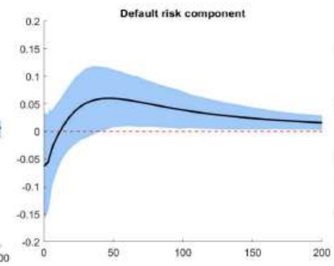
(a) Investment Companies



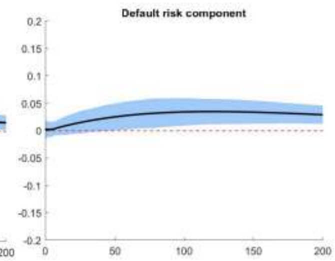
(b) Iron and Steel



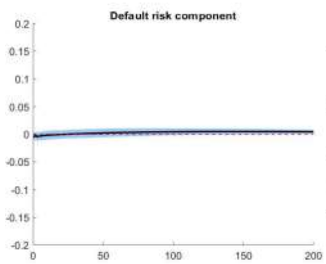
(c) Machinery



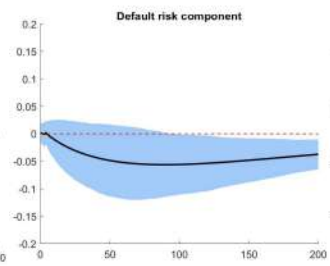
(d) Media



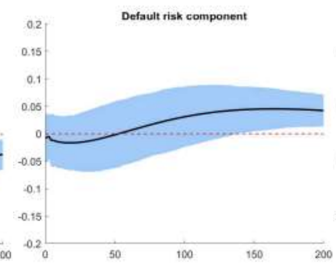
(e) Mining



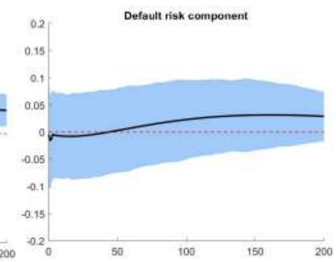
(f) Miscellaneous



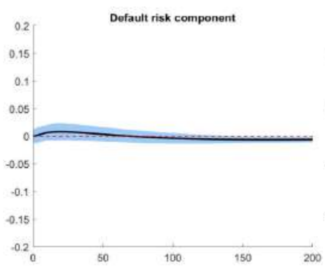
(g) Oil and Gas



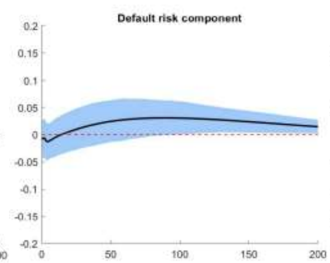
(h) Packaging



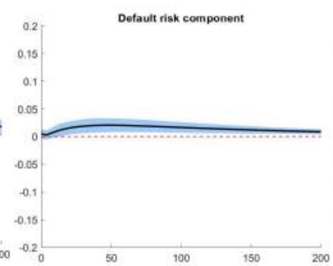
(i) Pharmaceuticals



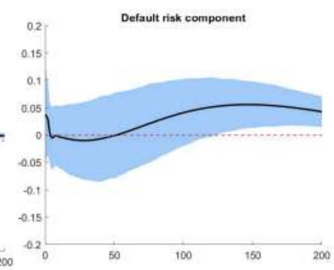
(j) Real Estate



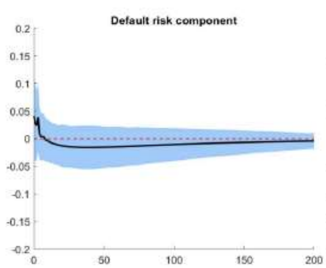
(k) Retail



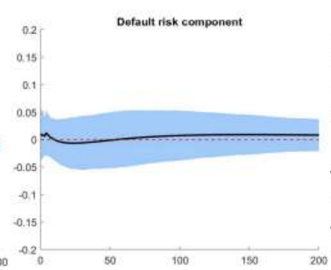
(l) Software



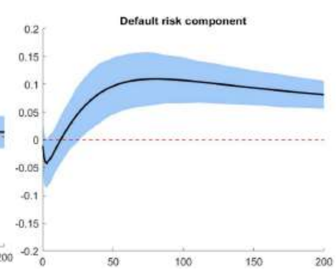
(m) Telecommunication



(n) Transportation Services



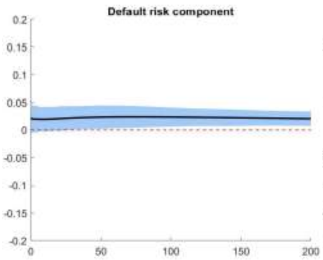
(o) Wood and Paper



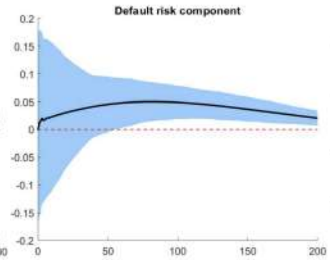
Notes: Impulse response function to an adverse sanction shock together with the 90% bootstrapped standard errors. All variables are standardised to have a zero mean and a unit variance. Only industries for which at least three different firms have bonds outstanding at each point in time are depicted.

Figure A18: All countries

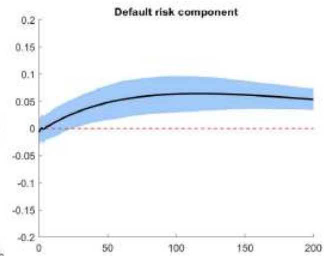
(a) Austria



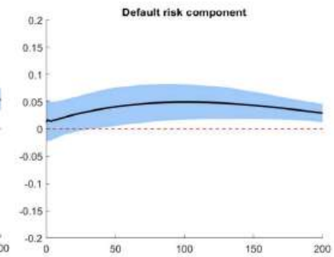
(b) Czech Rep.



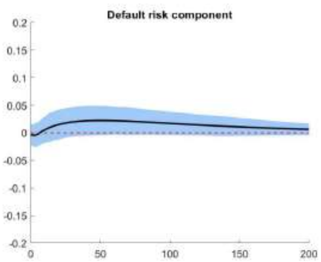
(c) Germany



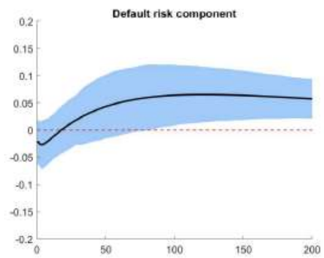
(d) Denmark



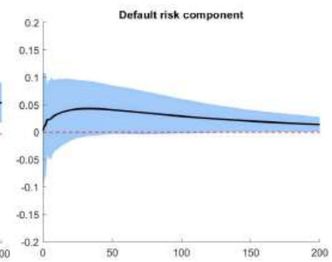
(e) Spain



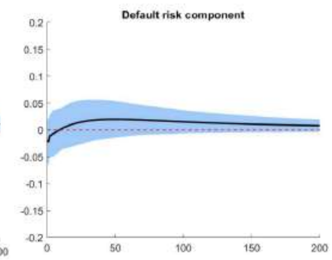
(f) Finland



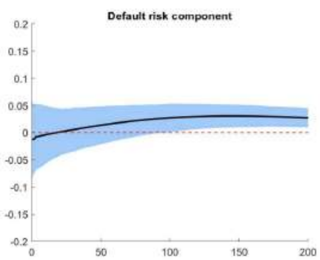
(g) France



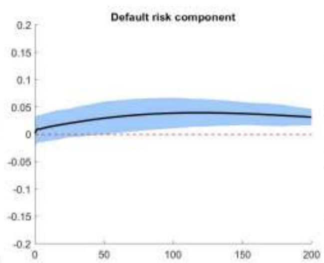
(h) Ireland



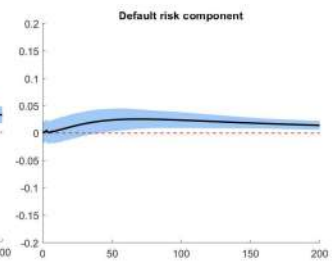
(i) Italy



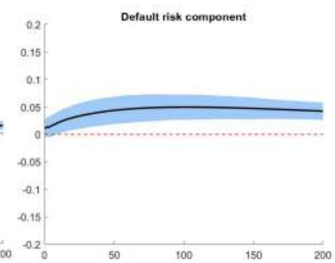
(j) Luxembourg



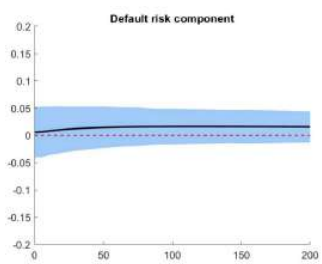
(k) Netherlands



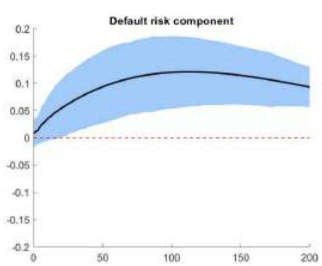
(l) Other non-EU



(m) Portugal



(n) Sweden



Notes: Impulse response function to an adverse sanction shock together with the 90% bootstrapped standard errors. All variables are standardised to have a zero mean and a unit variance. Only industries for which at least three different firms have bonds outstanding at each point in time are depicted.

Table A15: Conflict impact for firms highly exposed to Russia (post 2022)

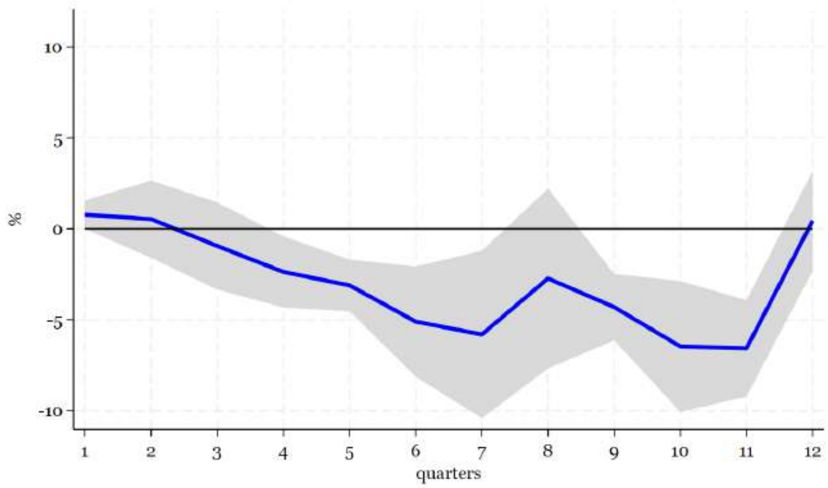
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1-week ahead		2-weeks ahead		3-weeks ahead		4-weeks ahead	
	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
L.sanction_shock	0.016^{***}	0.018^{***}	0.021^{***}	0.022^{***}	0.019^{***}	0.022^{***}	0.018^{***}	0.021^{***}
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)
High RU risk	0.001	0.003^{**}	0.000	-0.000	0.001	-0.003	0.002	-0.005
	(0.002)	(0.001)	(0.003)	(0.002)	(0.004)	(0.003)	(0.005)	(0.005)
High RU risk*L.sanction_shock	0.007^{*}	0.006^{*}	0.011^{**}	0.007	0.011^{***}	0.005	0.011^{**}	0.008^{*}
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
N	266357	237908	264081	237015	260428	234799	257467	233256
Firms	160	160	160	160	160	160	160	160
Country FE	Yes		Yes		Yes		Yes	
Industry FE	Yes		Yes		Yes		Yes	
Country-Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Controls*L.conflict_shock	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table examines the importance of firm-specific Russia dependence, measured by the index of Hassan et (2024), in a panel regression setting covering the period from January 2022 to April 2024. The dependent variable credit spread over various horizons (1, 2, 3, and 4 weeks ahead). Firms are classified as having a high Russia expos their Russia-specific risk index is above the 80th percentile on average in the years 2019 and 2020 (the last two ava years before the full-scale invasion of Ukraine). Firm controls include total assets, EBIT, interest expenses, and lev Standard errors are clustered at the country level.

Figure A19: Effect of a sanction shock on corporate investment

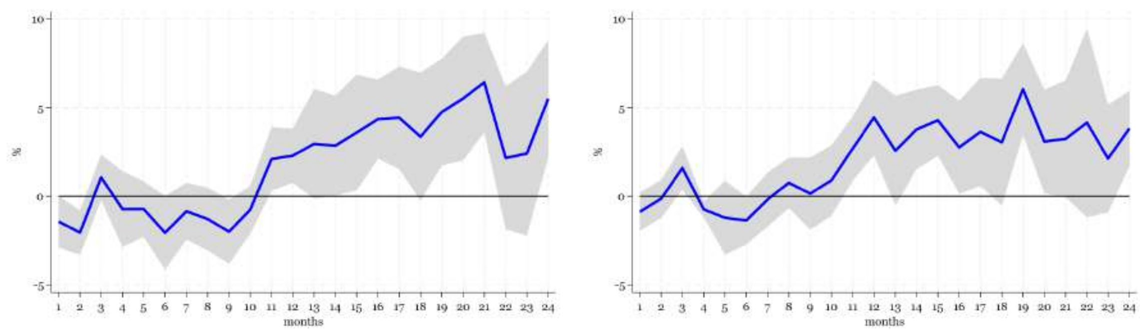


Notes: Impulse response function to a one standard deviation sanction shock with 90% (shaded area) confidence intervals. Standard errors are clustered at the country level. The blue line depicts the coefficient β_h in Equation 15 but including firm fixed effects. Firm controls include total assets, leverage, EBIT, interest expenses, and the average corporate credit spread (all controls are included with first-differences).

Appendix C.2. Additional results - bankruptcies

Figure A20: Effect of a sanction shock on bankruptcy rates

(a) Control alternative shocks (b) Excluding COVID-19 period

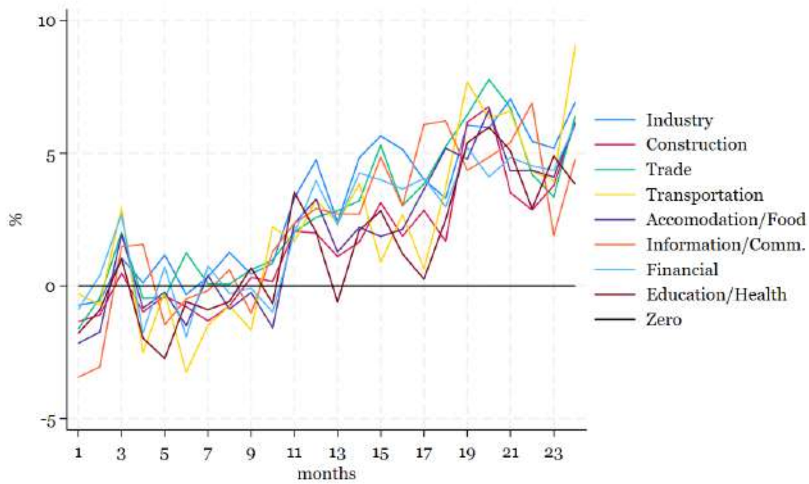


Notes: Impulse response function to a one standard deviation sanction shock with a 90% confidence interval. Standard errors are clustered at the country level. The black line depicts the coefficient β_h in Equation 17. Country controls include the logarithmically transformed industrial production and CPI, and the 10-year sovereign bond yield and net effective exchange rate (all controls are included with first-differences). Left: Additional controls are the European EPU index, the GPR index, the EU gas price shocks of Alessandri and Gazzani (2025), and EA monetary policy shocks of Jarociński and Karadi (2020). Right: Sample period excludes January 2020 to September 2021.

Only 9 EU countries report bankruptcy data on a monthly frequency, whereas data for 18 EU member countries is available quarterly. To verify the results presented in Figures 10 and A21, I re-estimate the local projections with one-quarter lags using the full sample of quarterly available bankruptcy data. The results confirm that bankruptcy numbers rise after one year and increase further after (Figure A22). The estimated cumulative response after two years is somewhat stronger than in the monthly model.

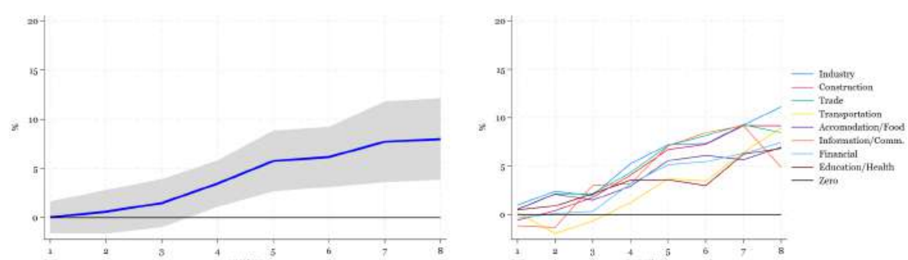
Lastly, I estimate the model to analyse the effect of the sanction intensity shock on monthly trade with Russia using UN Comtrade data. As expected, aggregate export and import volumes drop drastically after increased conflict. The cumulative monthly reduction in trade reaches up to around 10% of the average monthly import volumes from Russia and 12% of the average export volumes to Russia between January 2014 and April 2024. On the import side, the largest reduction is by far observed for mineral fuel and oil products (Figure A23). However, also other commodities imported from Russia are affected by the sanction shock. On the export side, the

Figure A21: Effect of a sanction shock on bankruptcies



Notes: Impulse response function to an adverse sanction shock. The blue line depicts the coefficient β_h in equation 17. Country controls include the logarithmically transformed industrial production and CPI and the 10-year sovereign bond yield and net effective exchange rate (all controls are included with first-differences). Significant responses are observed for all industries except Education/Health on a 10% significance level after two years.

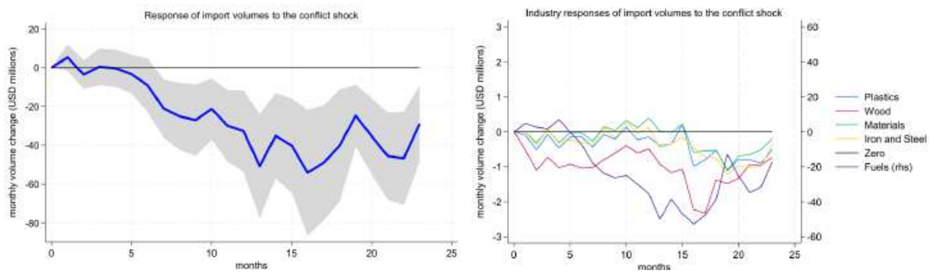
Figure A22: Effect of a sanction shock on bankruptcies (quarterly data)



Notes: Impulse response function to an adverse sanction shock with a 90% confidence interval. Standard errors are clustered at the country level.

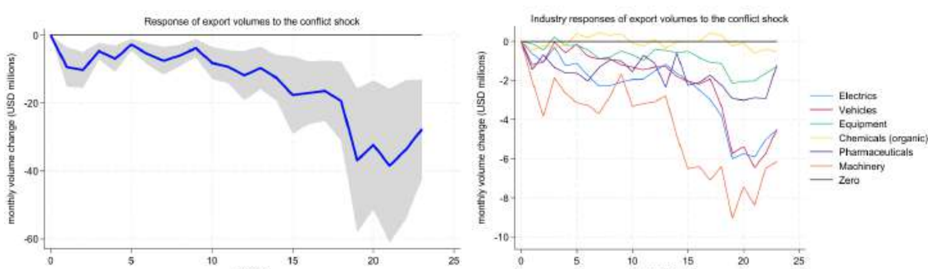
reduction in trade is strongest for machinery products, electrical equipment and machinery, and vehicles (Figure A24). These sectors all experienced a significant increase in the default risk component.

Figure A23: Effect of a sanction intensity shock on EU countries' import volumes from Russia



Notes: Impulse response function to an adverse sanction shock with a 90% confidence interval. Monthly trade data between the EU and Russia from 2014 to 2024 is taken from UN Comtrade. Standard errors are clustered at the country level.

Figure A24: Effect of a sanction intensity shock on EU countries' export volumes to Russia



Notes: Impulse response function to the sanction shock with a 90% confidence interval. Monthly trade data between the EU and Russia from 2014 to 2024 is taken from UN Comtrade. Standard errors are clustered at the country level.

To whom it may concern,

I, hereby confirm that I, the author of the paper “The price of geoeconomic dependence: Sanction intensity and corporate credit spreads”, am below the age of 35 as of June 10, 2026.

I further consent to handling of my personal data pursuant to regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016.

Moreover, I inform the committee that the paper has also been submitted to the ECB Young Economist Prize competition.

(Benedikt Kagerer)

Cambridge, 29.03.2026