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Geopolitical risk, bank lending and real effects on firms: evidence from the Russian invasion of Ukraine

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Abstract

This paper investigates whether geopolitical risk causes a reduction in bank lending. In particular, it focuses on how the increase in geopolitical risk stemming from the Russian invasion of Ukraine affected euro area bank credit supply. Matching granular supervisory and credit register data and using a panel difference-in-difference approach, the results show that banks with larger exposure to the increase in geopolitical risk cut lending significantly more than those with smaller exposure. Banks with greater exposure raised impairments despite exhibiting similar levels of credit distress to their peers, suggesting that the fall in lending was driven by uncertainty. Moreover, firms that were heavily reliant on banks with high exposure to geopolitical risk were unable to fully substitute this shortfall in credit by borrowing more from less affected banks, which significantly constrained firm investment and employment.

Keywords: Banks, financial markets, uncertainty

JEL Codes: G1, G21; E22

Non-technical summary

Geopolitical events — such as wars or rising tensions between countries — can significantly affect economic and financial systems. These events increase uncertainty and change how risks are perceived, which can lead banks to reduce lending. This paper studies whether the surge in geopolitical risk caused by the Russian invasion of Ukraine in early 2022 led to a contraction in bank lending in the euro area and, in turn, affected firm-level economic outcomes such as investment and employment.

The euro area provides a particularly relevant case study because of its geographical and economic proximity to the conflict, making the shock highly salient for its financial institutions. To understand these dynamics, the analysis uses highly detailed and confidential data from AnaCredit, the euro area credit register that collects loan-level information from euro area banks. These data are matched with detailed bank financial statements and firm-level information on employment and investment.

The empirical strategy compares how banks with greater exposure to geopolitical risk — measured using a bank-level index based on bank exposures and country-level geopolitical risk indicators — adjusted their lending compared to less exposed banks after the onset of the Russian invasion of Ukraine. By using data on firms with multiple banking relationships and applying a difference-in-differences, the analysis isolates changes in credit supply from changes in demand.

The results show that banks more exposed to the geopolitical risk shock significantly reduced their lending to firms in the quarters following the invasion more than their peers. This drop in lending occurred both in existing relationships (intensive margin) and in the formation of new bank-firm relationships (extensive margin). The effect persisted for about three quarters before gradually fading.

One reason for this contraction appears to be an increase in risk aversion: more exposed banks reported larger increases in loan impairments after the invasion, despite similar actual levels of borrower distress. This mechanism explains the tendency of these banks to pull back from lending during uncertain times. Importantly, banks with larger capital buffers were less likely to reduce lending, suggesting that better-capitalized banks are more resilient to uncertainty and can continue supporting firms during geopolitical risk shocks.

The study also finds that lending cuts were not uniform across sectors. Firms operating in industries that relied more heavily on inputs from countries closely aligned with Russia experienced a larger credit contraction. This indicates that banks were wary of lending to sectors vulnerable to supply chain disruptions tied to the conflict.

At the firm level, firms that were highly dependent on banks more affected by geopolitical risk were not able to fully replace lost credit by borrowing from other, less exposed banks. As a result, these firms experienced declines in both investment and employment, showing that geopolitical risk can have real, measurable effects on business operations and economic activity.

To ensure these findings are robust, the study conducts several additional tests. These include using matching techniques that account for differences between treated and untreated banks, controlling for other possible influences such as the energy price shock linked to the war, and testing for trends before and after the invasion. The results consistently support the main conclusion: the surge in geopolitical risk affected bank behaviour, and through the banking channel, impacted firms' real decisions.

1 Introduction

Adverse geopolitical events can trigger rapid shifts in risk sentiment and sharp increases in uncertainty, exposing existing vulnerabilities in banks that may cause them to curtail lending supply. Moreover, they can dent the investment and employment plans of firms, with knock-on effects for economic growth (Caldara and Iacoviello, 2022).

This paper investigates whether the significant increase in geopolitical risk associated with the Russian invasion of Ukraine affected euro area bank credit supply and consequently had significant effects on non-financial firms. This is an ideal laboratory to explore the effect of geopolitical risk because of the geographical proximity of the euro area to the event, which was the most severe geopolitical shock to hit Europe in decades. Using a continuous panel difference-in-difference approach at bank-firm level, the analysis assesses how banks that were more exposed to the increase in geopolitical risk stemming from this event adjusted their lending behaviour. Moreover, relying on firm-level regressions, it examines whether firms reliant on banks with higher exposure to geopolitical risk recorded a contraction in bank borrowing and if they reduced investment and employment.

The analysis uses on AnaCredit, the confidential pan-euro area credit registry data collected by the European System of Central Banks. In the baseline analysis, these loan-level data are aggregated to the bank-firm level, which makes it possible to disentangle credit supply from credit demand. Specifically, this analysis exploits data for firms with multiple bank relationships to control for firm credit demand by including firm×time fixed effects, following the approach introduced by Khwaja and Mian (2008). AnaCredit data are matched with bank-level balance sheet and profit and loss information from ECB supervisory statistics. Our final matched sample consists of a panel dataset at the bank-firm level, covering 363 banks and over half a million firms at quarterly frequency from 2021Q1 to 2023Q1, i.e. from one year before to one year after the start of the Russian invasion of Ukraine. In this context, to evaluate the exposure of individual banks to the increase in geopolitical risk stemming from the invasion, a variation of the bank-level geopolitical risk index first introduced by Dieckelmann et al. (2025) is used. This index is built by combining country level geopolitical risk indices provided by Caldara and Iacoviello (2022) with ECB supervisory data on bank asset exposures across countries. Finally, to investigate the real effects on firms of an increase in geopolitical risk, we also exploit data on firm characteristics, such as investment and numbers of employees, sourced from Orbis Europe.

The analysis yields a number of important insights. First, banks with higher exposure to geopolitical risk reduced their lending supply to non-financial corporations significantly more than those with lower exposure in the immediate aftermath of the Russian invasion of Ukraine. This pattern holds for both the intensive margin (lending adjustments in existing bank-firm relationships) and extensive margin (creation of new bank-firm relationships). Second, when examining how these effects evolve over time, we find that this impact lasts for three quarters. Third, we show that banks with higher exposure to geopolitical risk increased their loan impairments after the invasion more than their less exposed peers, despite exhibiting similar levels of credit distress. We claim, consistent with the argument put forward by Correa et al. (2023), that this finding reflects an increase in risk aversion on the part of more exposed banks, which faced with greater uncertainty, chose to contract lending. We also find that, ceteris paribus, the increase in geopolitical risk had a less material effect on the lending supply of banks with larger capital buffers pointing to a capital constraint channel. Banks with lower capital buffers have a greater incentive to safeguard capital by constraining lending more. Fourth, the findings indicate that lending contracted to a larger extent to borrowers in sectors that were more reliant on inputs imported from countries geopolitically aligned with Russia. This suggests that banks constrained lending to sectors reliant on more vulnerable supply chains. Fifth, aggregating data at firm level, we find that firms heavily reliant on banks with high exposure to geopolitical risk were unable to fully substitute this reduction in credit supply by borrowing more from less affected banks, leading to real economic effects in the form of reduced investment and employment.

Results from a battery of robustness tests and alternative specifications further support the baseline findings. The results are robust to employing a generalised propensity score weighting, allaying concerns that the treatment and control groups might have different underlying characteristics that drive the difference in their lending behaviour after the invasion. Similarly, results of placebo tests indicate that the baseline results were not driven by pre-existing nor post-existing trends rather than geopolitical events. Furthermore, we also control for banks' exposures to highly energy-intensive sectors or firms prior to the onset of the the Russian invasion of Ukraine to ensure that the results of the analysis are not driven by the simultaneous energy price shock, which was also led by the war. The results corroborate our baseline findings, showing that the energy price shock was not a driver of our results.

1.1 Related Literature

This paper contributes to a number of strands of the literature.

First, it builds on the seminal work by Caldara and Iacoviello (2022) who introduced a novel geopolitical risk index, which provides a measure of adverse geopolitical events and associated risks based on a tally of newspaper articles covering geopolitical tensions.[1] In this context, geopolitical risk is defined as the threat or realisation of adverse events associated with wars, terrorism and tensions between states. More specifically, the geopolitical risk metric used in this analysis, similarly to the approach used by Dieckelmann et al. (2025), captures the actual exposures of banks to geopolitical risk. Although related, it is important to mention that the concept of geopolitical risk is distinct from that of geopolitical fragmentation, as captured by Fernández-Villaverde

[1]Many recent papers (Arslanalp et al., 2023; Georgiadis et al., 2024; Hu et al., 2023) studying the macroeconomic and financial effects of geopolitical risk rely on this novel index introduced by Caldara and Iacoviello (2022)

et al. (2024), which has also been shown to have an effect on financial variables and investment (Aiyar et al., 2023; Baba et al., 2023).

This work can also be seen as contributing to the literature on uncertainty and bank lending. In a similar vein to our findings for geopolitical risk, a number of papers (Barraza and Civelli, 2020; Bordo et al., 2016; Buch et al., 2015; Correa et al., 2023) have shown that increases in uncertainty, especially if related to economic policy, have a negative effect on bank credit extension. This paper contributes to this literature by focussing specifically on the effects of geopolitical risk on bank lending supply. A number of papers show the effect of such risk on financial market indicators (Campos et al., 2023; Catalán and Tsuruga, 2023; D'Orazio et al., 2024; Federle et al., 2024a; Feng et al., 2023; Salisu et al., 2023). However, to date, there are only a few papers that examine the effect of geopolitical risk on banks (Behn et al., 2025; Demir and Danisman, 2021; Dieckelmann et al., 2025; Nguyen and Thuy, 2023; Pham et al., 2021; Phan et al., 2022), and these works mostly use bank-level data. Instead this paper, similar to both Niepmann and Shen (2025) and De Haas et al. (2025), takes advantage of more granular data. Niepmann and Shen (2025) analyse loan-level data to examine the effect of geopolitical risk with a particular focus on cross-border bank lending. They show that globally active US banks tend to continue to lend through foreign affiliates, even as they reduce cross-border lending to markets experiencing elevated geopolitical risk, and argue that this asymmetry is due to differential expropriation risk. Consistent with our results, they also find that global banks reduce lending to domestic firms in response to rising geopolitical risk. Similarly, De Haas et al. (2025) use loan-level data on a global sample of syndicated loans and find that, while overall cross-border lending to areas affected by violent conflict decreases, lending to firms in military or dual-use industries increases. In this context, it is key to mention that the use, in our work, of loan-level data for euro area banks, combined with a well established difference-in-difference estimation method (Acharya et al., 2022; Giannetti et al., 2023), means that we can identify and estimate the causal effect of an increase in geopolitical risk on bank lending supply.

Moreover, the analysis in this paper follows the chain of transmission of geopolitical risk through bank lending to firm behaviour contributing in this way also to the literature which shows that geopolitical risk can have an effect on real macroeconomic variables (Federle et al., 2024b; Matteo Iacoviello and Conlisk, 2024; Pinchetti, 2024). Our paper, exploiting micro data, provides evidence that a geopolitical risk shock can affect firms via a contraction in bank lending. In doing so, the analysis in this work complements other papers that carefully and systematically follow the transmission of the effects of international shocks to bank lending (Correa et al., 2023; di Giovanni et al., 2022; Federico et al., 2025; Kalemli-Özcan et al., 2013).

The rest of the paper proceeds as follows: Section 2 describes the data and Section 3 explains the estimation method. Sections 4 and 5 present the main results and the results from a series of robustness tests, while Section 6 concludes.

2 Data

2.1 Bank-firm, bank-level and firm level data

The analysis relies on data from a combination of confidential data sources available at the ECB. First, the analysis uses the loan level data in the AnaCredit credit register compiled by the European System of Central Banks. These data contain information on all individual bank loans extended in the euro area to non-financial corporations with a value exceeding EUR 25,000. Around 25 million individual loans are reported monthly, granted by around 7000 individual credit institutions to approximately 5 million of individual debtors. Anacredit includes only loans where the debtors are non-financial corporations and the creditors are banks. We exclude from the sample loans where more than one creditor is reported, i.e. syndicated loans. In the baseline analysis, the loan-level data are aggregated to the bank-firm level, and aggregated across different credit instrument types and maturities.[2,3] AnaCredit contains information on multiple loan characteristics such as outstanding loan volume, interest rate (type), maturity, impairment amounts, and probability of default. For the majority of instrument types, we capture credit supply by looking at outstanding loan amounts. However, as credit supply through credit lines is determined by the commitment amount at initiation of the contract, we use the commitment amount rather than the outstanding amounts for credit lines. The analysis also takes advantage of information in AnaCredit on borrowing firms (size, location, industry) and lending banks (location). The data include information assigning firms to industrial sectors according to the Statistical Classification of Economic Activities in the European Community (NACE Rev.2). The AnaCredit data do not require the reporting of lending by bank subsidiaries located outside the euro area.[4] Information on direct cross-border lending from euro area resident banks is available but accounts only for about 1.5% of the value of outstanding loan amounts reported in the data. Therefore, the vast majority of the loans recorded in the data relate to domestic euro area lending.

We complement the bank-firm level data with bank-level balance sheet and profit and loss data from the ECB supervisory statistics.

Furthermore, the analysis of the real effects at the firm level relies on data on firm characteristics sourced from Orbis Europe, including information relating to investment and numbers of employees. Specifically, we match data on firms available in Orbis

[2]In AnaCredit, credit instruments are categorised into revolving credit other than overdrafts and credit card debt, credit lines other than revolving credit, term loans, overdrafts, credit card debt, trade receivables, and finance leases.

[3]Prior to aggregation all loan-level and bank-level variables are winsorised at the 1% level to remove outliers and anomalies. For items such as loan maturity and interest rate (type), the aggregation from loan-level to bank-firm level is done using a weighted average principle.

[4]While the AnaCredit Regulation does not mandate the reporting of data on foreign entities outside the euro area, it does not prohibit it either. Therefore, if a credit institution wishes to report data on its foreign branches or subsidiaries, it may do so, provided that the relevant NCB has established procedures to accept such data. See AnaCredit Manual Part I.

with loan-level data of euro area banks reported in AnaCredit, following papers such as Altavilla et al. (2024, 2022), yielding a sample of well over half a million observations.

The data in the analysis are at a quarterly frequency to align with the reporting frequency of the bank-level control variables. The matched sample for the main analysis includes 363 institutions across 20 euro area countries (Figure 1) for the period from 2021Q1 to 2023Q1 (i.e. one year before and one year after the start of the Russian invasion of Ukraine).[5]

Table 1 shows the descriptive statistics for the variables used in the baseline regressions. The summary statistics for the bank-specific variables are in line with previous work using euro area credit registry data (Coulier et al., 2024; Dautović et al., 2023).

2.2 Measuring banks' exposure to geopolitical risk

The exposure of euro area banks to geopolitical risk is heterogeneous. To evaluate banks' actual exposures to this risk, we rely on a variation of the bank-level indicator of geopolitical risk first introduced by Dieckelmann et al. (2025). More specifically, this indicator is built by weighting the change in the standardised country-level geopolitical risk (CGPR) indices of Caldara and Iacoviello (2022) with bank-level asset-side exposures to the different countries where banks operate, sourced from the ECB Supervisory statistics:

$$\mathrm{BGPR}_b = \sum_{c=1}^{n} \left(\Delta\mathrm{CGPR}_c \times \frac{\mathrm{Exp}_{b,c}}{\mathrm{TotalExp}_b} \right) \tag{1}$$

where $\Delta\mathrm{CGPR}_c$ is the change in the standarised country-level geopolitical risk index between 2021Q4 and 2022Q1 for country c, i.e., the increase in geopolitical risk resulting from the Russian invasion of Ukraine, and $\frac{\mathrm{Exp}_{b,c}}{\mathrm{Total\ Exp}_b}$ is the average, over the period

[5]Note that we use entity-level data as this is the level at which most lending decisions are made. Individual banks or subsidiaries are typically responsible for assessing credit risk and approving loans, making entity-level data more relevant than data at group-level for understanding lending practices in this context.

2021Q1-2021Q4, of the share of bank b exposures to country c over its total exposures.

Caldara and Iacoviello (2022) calculate the country-specific indices of geopolitical risk by counting the monthly share of all newspaper articles that are both: (1) on the subject of geopolitical events and (2) mention the name of the country or its major cities. The resulting indices capture the perceived risks posed by, or involving, the country in question. These indices are available at the country level for 44 countries (including 8 euro area countries). To make the analysis more comprehensive, the same methodology is applied to a corpus of newspaper articles sourced from the Factiva news monitoring platform to extend the coverage of the index to all missing euro area and EU countries following Dieckelmann et al. (2025). This expands the number of countries that can be included in the analysis to 62, which allows us to cover at least 85% of the total exposures of each bank in the sample.

The country-level geopolitical risk indices are then standarised by transforming them into z-scores to better allow comparisons across countries (Dieckelmann et al., 2025).[6] Figure 2 illustrates that the increase in the standardised country level GPR indices after the Russian invasion of Ukraine was generally higher in countries geographically closer to Ukraine. Similarly, when these changes are weighted by the asset exposure of the euro area banks as shown in Figure 3, the BGPR is also generally stronger in banks located in euro area countries in Central and Eastern Europe that were closer to the invasion, consistent with Federle et al. (2024b). This high degree of variation in the cross-country and cross-bank exposure (see Figure 4) to the geopolitical shock arising from the Russian invasion of Ukraine makes this an ideal laboratory in which to explore the effects of geopolitical risk on bank lending behaviour.

[6]The country-level geopolitical risk indexes are standardized by transforming them into z-scores based on their historical time series extending back as far as 1985 (where available). As a result, the standardized country-level GPR index values represent the number of standard deviations above or below the (country-specific) long-run average of geopolitical risk.

3 Estimation strategy

3.1 Empirical framework for the baseline bank-firm level analysis

The key objective of the empirical analysis carried out in this study is to investigate whether banks that had a greater exposure to the geopolitical risk stemming from the Russian invasion of Ukraine changed their lending supply in response to it more than their peers. To test this hypothesis a continuous difference-in-difference setting is employed, using the following panel fixed effect model:

$$\begin{aligned} y_{b,i,t} = {} & \beta_1 BGPR_b + \beta_2 Post_t + \beta_3 (BGPR_b \times Post_t) + \beta_4 X_{b,t-1} + \beta_5 (X_{b,t-1} \times Post_t) \\ & + \delta_{i,t} + \mu_{b,i} + \gamma_{c,t} + \varepsilon_{b,i,t} \end{aligned} \tag{2}$$

where the dependent variable $y_{b,i,t}$ is the logarithm of the outstanding amount of loans from bank b to firm i at time t as in Federico et al. (2025). The variable of interest is the interaction between the $BGPR_b$, the exogenous bank-level geopolitical risk index, and $Post_t$, a dummy variable that takes a value of one between 2022Q1 and 2022Q4, i.e. from the onset of the Russian invasion of Ukraine to the end of the sample period, and zero for the preceding quarters.[7] β_3, our coefficient of interest, captures whether the exposure to geopolitical risk affected bank lending supply since the onset of the Russian invasion of Ukraine. $X_{b,t-1}$ is a vector of lagged bank-level characteristics, which may also affect bank-firm lending, included in previous studies such as, for example, in Altavilla et al. (2022), Couaillier et al. (2025), Coulier et al. (2024) and Correa et al. (2023). More specifically, the variables included at the bank level are the log of total assets to control for bank size, the TIER 1 capital ratio to control for bank solvency, the deposit-to-liability ratio to capture the extent of bank reliance on deposit funding, the provisions-to-loans ratio to capture the asset quality of bank loan portfolios, the

[7] The post-invasion period is considered to start in 2022Q1. Although the invasion began in February 2022, AnaCredit data are reported at the end of each quarter. As such, using 2022Q1 as the starting point appropriately captures the initial effects without introducing timing inconsistencies.

return on assets (ROA) to control for bank profitability, and the ratio of cash (including cash held at central banks) to total assets to capture bank liquidity. Importantly, we also allow these control variables to have heterogeneous effects on lending following the onset of the Russian invasion of Ukraine by interacting them with the post dummy ($X_{b,t-1} \times Post_t$) as in Correa et al. (2023). This ensures that our coefficient of interest is not driven by the heterogeneous impact on lending of other time-varying bank-specific characteristics.

Equation 2 is saturated with a granular set of fixed effects to account for both observed and unobserved heterogeneity across banks and firms. The vector $\delta_{i,t}$ denotes firm×quarter fixed effects. This is crucial for the identification strategy, as it allows us to disentangle credit demand from credit supply. Specifically, it controls for the demand for credit from firms that have lending relationships with multiple banks (Khwaja and Mian, 2008). The high dimensional fixed effects included in our set-up also ensure that our results are not driven by time-invariant bank-firm relationship effects, which are captured by bank×firm fixed effects ($\mu_{b,i}$), while country specific factors are absorbed by a vector of country×quarter fixed effects ($\gamma_{c,t}$), where the country refers to the nationality of the lending bank. Country×quarter fixed effects control for time-varying country-specific effects such as the business and monetary policy cycles that could be correlated with geopolitical risk, potentially affecting bank lending. Standard errors are clustered at the bank-level. Borrower×quarter fixed effects are included in all our model specifications.[8] These fixed-effects completely subsume the dummy variable $Post_t$ which, therefore, does not appear separately in the analyses. Similarly, the inclusion of either bank fixed effects or bank×firm fixed effects implies that, in some specifications, the bank-level geopolitical risk indicator $BGPR_b$ is subsumed.

[8] Borrower×bank and country×quarter fixed effects are instead only included in some specifications.

4 Results

4.1 Bank-firm level analysis

4.1.1 Intensive margin

Table 2 reports the regression results of equation 2. The regression in Column (1) includes only borrower×quarter fixed effects in addition to the variable of interest. Bank fixed effects are added in Column (2) to account for time-invariant bank-specific unobserved characteristics, while Column (3) also adds time-varying bank controls and their interactions with the *Post* variable. In addition to the aforementioned bank controls, column (4) includes borrower×quarter and borrower×bank fixed effects. Our preferred specification is the heavily saturated specification reported in Column (5), which simultaneously includes bank controls as well as borrower×quarter, borrower×bank and country×quarter fixed effects.

The regression results in Table 2 show that, on average, heightened geopolitical risk following the Russian invasion of Ukraine exerted a significant impact on the supply of bank lending to euro area non-financial corporations. The estimated coefficient of $BGPR_b \times Post_t$ in Column (5) is negative, statistically significant at the 1% level and economically sizeable: a 1 standard deviation increase in the $BGPR$ resulted in an approximately 9.2% reduction in corporate lending at the bank-firm level following the event. It is worth noting that the coefficients hold-up well in all specifications, corroborating the robustness of the finding. They are also somewhat larger in size in Column (5), highlighting the importance of accounting for observable and unobservable bank- and country-specific characteristics that potentially affect bank lending behaviour in addition to geopolitical risk.[9]

4.1.2 Parallel trends

Figure 5 displays the dynamics of the estimated effect on lending over different time horizons, taking 2021 Q4 as the reference period. Importantly, prior to the invasion, there were no significant differences in lending behaviour between banks with different levels of geopolitical risk exposure. This finding also validates our identifying assumption that banks' lending behaviour was not affected by their exposure to geopolitical risk before the onset of the Russian invasion of Ukraine. However, the situation changed afterwards. The reduction in lending volumes became statistically significant after the onset of the invasion and the effect persisted for three quarters, until the uncertainty concerning the potential effects of the conflict eased. This temporary but significant contraction underscores the sensitivity of lending supply to geopolitical risk.

4.1.3 Impact on bank impairment volumes

By increasing uncertainty, greater exposure to geopolitical risk could reduce the perception of banks of the creditworthiness of their borrowers. Correa et al. (2023) study the effects of an increase in trade policy uncertainty on bank lending. They find that, following this type of shock, banks increase impairments and contract lending, consistent with a wait and see strategy. This occurs even though bank do not experience any observable deterioration in asset quality, as would be expected to occur after a balance

[9]The estimated magnitude of the coefficient is comparable to other papers examining the response of bank lending to geopolitical risk and other sources of uncertainty. For instance, Niepmann and Shen (2025) find that a one standard deviation increase in geopolitical risk reduces U.S. banks' loan origination to U.S. firms by around 20 percent on average. Regarding trade uncertainty, Correa et al. (2023) find that a one standard deviation increase in bank exposure to trade uncertainty is associated with a 5.0 percentage point decline in bank-firm loan growth. Relatedly, Federico et al. (2025) find that a one standard deviation increase in bank exposure to China's entry into the WTO implies 7.4 percent lower credit supply. Our findings are contrary to those of Demir and Danisman (2021), who use bank level data and find that, in contrast to economic policy uncertainty, geopolitical risk is not significantly associated with a decline in the growth of bank credit to non-financial corporations.

sheet shock.

To test whether a similar pattern is observed in the event of a geopolitical shock, we first estimate a set of regressions similar to Equation 2, using the logarithm of the volume of impairments as the dependent variable, while also controlling for the logarithm of the total outstanding amount of loans.[10] Loans are assessed by banks as being impaired if the expected recoverable value falls below its book value. Table 4 shows the effect of geopolitical risk arising from the Russian invasion of Ukraine on banks' impairment volumes. The results show that banks that experienced a one standard deviation increase in their exposure to geopolitical risk significantly increased the volume of impairments, by around 24% after the start of the invasion, compared to their peers. This suggests that banks that faced greater uncertainty due to heightened geopolitical risk proactively chose to increase their impairments compared to other banks.

In a second step, we assess whether an increase in a bank's exposure to geopolitical risk leads to a materialisation of credit risk. To investigate this question, we use a regression framework where the number of days past due is the dependent variable (computed as a weighted average for each bank–firm pair). In this analysis, we relax the fixed-effects specification, as variation in past due days is meaningful only for a subset of firms - those with debt repayment issues.[11] Table 5 shows that the interaction term $BGPR_b \times Post_t$ is not statistically significant in any of the econometric specifications, indicating that, following the onset of the invasion, there was no significant difference in the number of days past due across banks with varying exposure to geopolitical risk. Taken together,

[10]This control is important as the volume of impairments is correlated with the size of the lending.

[11]Moreover, including borrower × quarter fixed effects would not be appropriate in this setting, since it is not clear why the same firms should accumulate more past due loans with a bank with higher geopolitical risk exposure relative to another bank with lower exposure. We therefore adopt a specification with bank and time fixed effects, which allows us to test whether, on average, banks more exposed to geopolitical risk experience a greater deterioration in credit quality following the conflict, thus justifying a credit contraction. Recognising that bank and time fixed effects may still be too coarse - given that more exposed banks might lend more to firms operating in more affected industries, locations, or size segments - we further refine the specification by introducing industry × location × size fixed effects.

these results show that the decline in bank lending supply that we observe was not due to a deterioration in bank balance sheets but rather to a precautionary contraction in lending driven by heightened geopolitical uncertainty.

4.1.4 Extensive margin

The effects described above not only affect bank lending supply at the intensive margin, but also the probability that banks engage in new lending relationships, that is, the extensive margin of bank lending supply.

Table 3 reports the results of regressions where the dependent variable is the probability of a bank establishing a new lending relationship with a non-financial corporation.[12] This dependent variable is defined as a dummy equal to 1 if: a) at time t a new firm which did not have a relationship in the previous quarter enters the AnaCredit registry, or b) a firm that was in the sample in $t-1$ borrows from a different bank than in the past. In this setting, we do not control for borrower $\times$ quarter fixed effects because we want to capture the formation of new bank-firm relationships in general, rather than focus only on firms that already had banking relationships. To allow for the inclusion of new firms that did not have a bank relationship in the previous quarter, these regressions use industry $\times$ location $\times$ size (ILS)$\times$time fixed effects instead.[13] A one standard deviation increase in bank-level geopolitical risk significantly reduced the likelihood of a bank establishing a new lending relationship by 6.1 percentage points.[14]

[12]In the Appendix, we also report the results of regressions using the probability of a bank extending a new loan as the dependent variable, as an alternative measure of the extensive margin. The results of this extension are qualitatively similar.

[13]Industry is based on NACE 4 revision 2 statistical classification codes, location is based on NUTS 3 classification of regions, and size groups are defined in accordance with the Annex to Commission Recommendation 2003/361/EC (micro, small, medium, and large firms).

[14]That banks respond to increased geopolitical risk by restricting lending at both the extensive and intensive margin is similar to the findings for trade uncertainty reported by (Correa et al., 2023) and in response to trade shocks reported by (Federico et al., 2025).

4.1.5 Amplifiers and mitigators: Liquidity constraints, capital headroom, deposit funding structure and size

Certain bank characteristics could amplify or dampen the effect of geopolitical risk on bank lending supply. To investigate this hypothesis, we focus on four bank level variables, the cash-to-assets ratio, distance to maximum distributable amount (MDA), the logarithm of total assets, and the uninsured deposit ratio.[15] These variables are indicators of bank liquidity, capital, size and funding structure, respectively.

Having access to abundant liquid assets and ample capital buffers above the MDA can help banks to withstand geopolitical risk shocks. These shocks can increase market volatility, affecting the value of assets held by banks. They can lead to losses or require banks to hold more capital against these assets, potentially reducing their available liquidity and thus limiting their lending capacity. In addition, fair value losses on their assets are reflected in the calculation of high-quality liquid assets used as collateral, thereby restricting the ability of banks to obtain secured funding (e.g., from the ECB or via repurchase agreement operations) that could be employed for credit provision (Berger and Bouwman, 2009; Holmstrom and Tirole, 1997; Ivashina and Scharfstein, 2010).

Geopolitical risk shocks can also elevate credit risk, affecting the ability of borrowers to repay loans. This can lead to higher loan loss provisions and impact a bank's solvency and therefore prompt banks, especially those with lower capital buffers, to reduce lending. As breaching regulatory capital requirements triggers closer supervisory scrutiny and leads to constraints on dividend distributions, bonuses, and coupon payments (Couaillier et al., 2025), less capitalised banks may pre-emptively reduce their risk-weighted assets (i.e., the denominator of the capital ratio) to preserve their capital

[15] Distance to MDA is defined as the core equity tier 1 (CET 1) capital ratio minus the overall capital requirement (OCR) ratio and is expressed in percentage.

buffers.[16]

It is not clear ex-ante whether larger banks might be expected to be more resilient in the face of geopolitical shocks than smaller banks. On the one hand, they may have a more diversified portfolio of assets, better access to capital, and be subject to greater supervisory oversight and larger capital requirements. On the other hand, theory predicts that smaller banks may have a comparative advantage in producing the soft information necessary to lend to smaller privately held firms (Berger et al., 2005; Biswas et al., 2017; Stein, 2002). However, these advantages are likely to be less relevant for lending to larger firms, and larger firms are more likely to export goods internationally (Amiti and Weinstein, 2011; Melitz, 2003). Thus, larger banks may have more exposures to the geopolitical event, including through domestic lending to companies that trade in the countries directly affected.[17]

Finally, a higher uninsured deposit ratio could make banks' funding more sensitive to shocks by increasing the likelihood of sudden withdrawals raising funding costs and creating liquidity strains for banks and thus curtailing their lending.

To explore the potential effects on credit supply stemming from the interaction of the aforementioned characteristics with banks' exposure to geopolitical risk, we expand upon the specification described in equation (5) by including a triple interaction between $BGPR \times Post$ and each of the four bank-specific variables one at a time.

$$
\begin{aligned}
y_{b,i,t} = {} & \beta_1 BGPR_b + \beta_2 Post_t + \beta_3 Mitigator_b + \beta_4 (BGPR_b \times Post_t) + \beta_5 (BGPR_b \\
& \times Mitigator_b) + \beta_6 (Mitigator_b \times Post_t) + \beta_7 (BGPR_b \times Post_t \times Mitigator_b) \\
& + \beta_8 X_{b,t-1} + \beta_9 (X_{b,t-1} \times Post_t) + \delta_{i,t} + \mu_{b,i} + \gamma_{c,t} + \varepsilon_{b,i,t}
\end{aligned} \tag{3}
$$

The dependent variable, $y_{b,i,t}$, is the logarithm of the outstanding amount of loans

[16] Indeed such behaviour may be prudent. Using a historical dataset, Behn et al. (2025) find that heightened geopolitical risk has been associated with lower bank capitalisation over the past century, albeit less so in instances of geographically localised events.

[17] Recall that any tendency for larger banks to have larger exposures through foreign lending should already be captured through the inclusion of the BGPR×Post interaction.

from bank b to firm i at time t. The variable of interest is the triple interaction term $BGPR_b \times Post_t \times Mitigator_b$, where $Mitigator_b$ denotes the pre-invasion average of bank-specific characteristics — namely, the cash-to-assets ratio, distance to MDA, the logarithm of total assets, or the uninsured deposit ratio. Our coefficient of interest, β_7, captures how the effect of geopolitical risk exposure after the invasion ($BGPR_b \times Post_t$) varies depending on the value of the mitigator variables. The vector $X_{b,t-1}$ includes the same set of lagged bank-level control variables as in Equation 2. As in previous regressions, we include firm×quarter fixed effects ($\delta_{i,t}$), bank×firm fixed effects ($\mu_{b,i}$) and country×quarter fixed effects ($\gamma_{c,t}$).

The results in Table 6 show that the coefficient on the triple interaction $BGPR \times Post \times Mitigator$ is only statistically significant in the case of the distance to MDA and bank size. A larger distance to MDA mitigated the reduction in lending supply after the Russian invasion of Ukraine, pointing to a capital constraints channel (Correa et al., 2023; Holmstrom and Tirole, 1997), while the estimated effects are statistically significantly larger for bigger banks. The absence of significance on the cash-to-assets and uninsured deposit ratio coefficients suggests that liquidity and funding concerns were not key factors constraining bank lending supply after the onset of the invasion.

4.1.6 Sectoral lending

Some non-financial corporate sectors may have been more affected by the Russian invasion of Ukraine than others for a number of reasons. In particular, firms in sectors that are more reliant on inputs from outside the EU generally, especially from countries geopolitically aligned with Russia, could be more exposed to supply chain disruptions and could face greater credit constraints if banks seek to minimise their exposure to geopolitical risk. The next set of regressions tests this hypothesis.

The list of Russia-aligned countries is determined using the ideal point distance (IPD) based on UN voting patterns from Bailey et al. (2017). Countries in the low quartile of

IPD with Russia are categorised as aligned (see Table 7). Then, the following measure of sectoral input dependencies to Russian-aligned countries for each sector j in each country c is computed using data sourced from Eurostat Figaro Input-Output tables, following Arjona et al. (2023):

$$\text{Input dependencies}_{j,c} = \frac{\text{Russia-aligned inputs}_{j,c}}{\text{Total inputs}_{j,c}} \tag{4}$$

We focus on 19 industries, using data for 2021, prior to the start of the invasion.[18] In this analysis, we compute the measure specifically for industries within euro area countries. The regression analysis focuses on domestic lending and intra-euro area lending, which together represent the majority of the dataset. As previously noted, cross-border lending accounts for only 1.5% of total lending volumes and thus constitutes a minor share. Figure 6 shows the average of *Input dependencies*$_{j,c}$ across euro area countries. On average, the most vulnerable sectors appear to be Manufacturing, Electricity, Transportation, and Mining.

This measure is used to construct a dummy variable, $VulnerableSector$, which takes a value of 1 if the sector of the debtor falls within the top 25th (or 50th) percentile of the most dependent sectors in its country. This dummy is included in the baseline specification as an additional variable and as part of a triple interaction $BGPR \times Post \times VulnerableSector$. The latter is the main variable of interest in the below regression:

[18]The input-output table includes 21 industries but sector T (Activities of households as employers) and sector U (Activities of extraterritorial organisations and bodies) are excluded as they are not relevant for this analysis, which focusses on bank lending to non-financial corporations.

$$
\begin{aligned}
y_{b,i,t} = {} & \beta_1 BGPR_b + \beta_2 Post_t + \beta_3 VulnerableSector_i + \beta_4(BGPR_b \times Post_t) + \beta_5(BGPR_b \\
& \times VulnerableSector_i) + \beta_6(VulnerableSector_i \times Post_t) + \beta_7(BGPR_b \times Post_t \\
& \times VulnerableSector_i) + \beta_8 X_{b,t-1} + \beta_9(X_{b,t-1} \times Post_t) + \delta_{i,t} + \mu_{b,i} + \gamma_{c,t} + \varepsilon_{b,i,t}
\end{aligned} \tag{5}
$$

The dependent variable, $y_{b,i,t}$, is the logarithm of the outstanding amount of loans from bank b to firm i at time t. The coefficient of interest on the triple interaction, β_7, captures the differential effect for firms in vulnerable sectors in the post-period. The vector $X_{b,t-1}$ includes the same set of lagged bank-level control variables as specified in Equation 2. As before, we include firm $\times$ quarter fixed effects ($\delta_{i,t}$), bank $\times$ firm fixed effects ($\mu_{b,i}$), and country $\times$ quarter fixed effects ($\gamma_{c,t}$).

The results presented in Table 8 suggest that more geopolitically exposed banks curtailed lending to sectors dependent on inputs from Russia-aligned countries (both for domestic and euro area lending) 2% - 3% more than to other sectors.[19]

4.2 Firm-level analysis

In the bank-firm level analysis above, we showed that a higher exposure to geopolitical risk leads to a larger contraction in lending supply to non-financial corporations. However, such a reduction in bank lending may not have any aggregate effect on firm outcomes if firms can replace the contraction in credit from banks with a higher exposure to geopolitical risk by borrowing more from banks with a lower exposure. In practice, however, the ability of firms to find alternative sources of bank lending could be impaired as heightened geopolitical risk could potentially entail lower economic growth and a general deterioration of banks' asset quality. Therefore, banks with a lower exposure may be less willing to pick up the slack. To investigate this empirical question, the following

[19] This result differs somewhat to the findings of Federico et al. (2025) which show that banks did not differentiate between more and less exposed sectors when they curtail lending in response to trade shocks.

firm-level regression specification was estimated using on AnaCredit data:

$$y_{i,t} = \beta_1 Exposedfirm_i + \beta_2 Post_t + \beta_3(Exposedfirm_i \times Post_t) + \beta_4 X_{i,t-1} + \\ \beta_5(X_{i,t-1} \times Post_t) + \eta_{ILS,i,t} + \delta_i + \varepsilon_{i,t} \tag{6}$$

where $y_{i,t}$ is the logarithm of the total outstanding borrowing amount of firm i in quarter t. The key variable of interest in this first additional specification is $Exposedfirm_i \times Post_t$, i.e., the interaction between the "exposed" group and the post dummy variables. Firms were classified as "exposed" if, prior to the conflict (i.e., in Q4 2021), at least 50% of their loans were sourced from banks within the top 25th percentile of geopolitical risk exposure. $X_{i,t-1}$ represents the same set of lagged bank controls included in equation (2), but weighted by the share of total firm borrowing from each bank, to obtain a time-varying weighted average of bank characteristics for each firm. We also interact the control variables with the post dummy ($X_{i,t-1} * Post_t$). To control for potential heterogeneity in credit demand across firms, industry $\times$ location $\times$ size (η_{ILS}) $\times$ quarter fixed effects are included in equation 6.[20] In addition, some specifications also include firm fixed effects to absorb all unobservable time-invariant characteristics across firms (δ_i). Standard errors are clustered at firm level.

The results, reported in Table 9, suggest that firms reliant on banks with higher exposure to geopolitical risk exhibited a 1.5% reduction in borrowing in relative terms. The fact that this coefficient is smaller than the coefficient on $BGPR \times Post$ in the baseline results suggests that, on average, firms managed to access some credit from alternative sources at different banks. However the coefficient is negative and statistically significant. This indicates that such firms faced difficulties substituting loans from these lenders with borrowing from less exposed banks during stressed times, resulting in an

[20]Since the data are collapsed at the firm-level, firm$\times$ time fixed effects cannot be included in equation 6.

reduction in firm's overall borrowing.[21]

Next, the following set of cross-sectional firm-level regressions were run to examine whether firms reliant on banks with high exposure to geopolitical risk exhibited reduced investment and employment:

$$\Delta y_i = \beta_1 Exposedfirm_i + \beta_2 X_{i,2021} + \beta_3 X_{b,2021} + \eta_{ILS,i} + \varepsilon_i \tag{7}$$

where Δy_i is the firm-specific change between 2021 and 2022 of two variables, which are specified as follows: 1) *investment* which is the change in the ratio of fixed assets to total assets; and 2) *number of employees* which is the growth in the number of employees. $Exposedfirm_i$ is the key variable of interest. As above, firms were classified as "exposed" if, prior to the conflict (i.e., in Q4 2021), at least 50% of their loans were sourced from banks within the top 25th percentile of geopolitical risk exposure. $X_{i,2021}$ is a vector of firm control variables (log total assets, cash to assets, leverage, EBITDA, ratio of tangible assets) with values taken in 2021, before the start of the invasion. $X_{b,2021}$ is the same vector of weighted bank controls at a firm level as used in equation (5), while $\eta_{ILS,i}$ are again industry-location-size fixed effects. These firm-level variables are taken from Orbis and merged with our sample of borrowers. Basic descriptive statistics can be found in the Appendix.

The results reported in Table 10 suggest that geopolitical events can lead to quantitatively important effects on firm investment and employment. Firms that were reliant on banks with higher exposure to geopolitical risk exhibited a 8% reduction in investment and a 0.6% reduction in their number of employees, compared to average firms. This implies that the constraints on bank lending arising from geopolitical events can have material economic consequences for firms and their employees.[22]

[21] In their analysis of the effects of trade uncertainty on bank lending, Correa et al. (2023) also find that firms in borrowing relationships with more exposed banks faced difficulties gaining access to substitute sources of credit.

[22] These results are consistent with the findings of Correa et al. (2023); Federico et al. (2025) in their analyses of the response of bank lending to trade policy uncertainty and trade liberalization.

5 Robustness checks

5.1 Generalised propensity score weighting and placebos tests

Concerns may arise that there could be imbalances in treatment intensity and a selection bias linked to covariates that make the treatment not random. The first two robustness tests aim to rule out the possibility that banks that experienced a larger increase in $BGPR$ might have other differences in their underlying characteristics that explain the observed difference in their lending behaviour in the post-invasion period.

By implementing a Generalised Propensity Score Weighting, we balance pre-treatment covariates (using the mean of the covariates during the pre-period), to ensure that observed differences in outcomes are not due to pre-existing differences, but rather to the treatment itself. To do so, we use the covariate-balancing generalised propensity score weighting of Fong et al. (2018), whereby observations are re-weighted based on their probability of receiving a certain treatment intensity. This approach constructs weights that minimise the correlation between the treatment intensity and pre-treatment bank-level control variables, ensuring a more balanced comparison across different levels of treatment.

When the baseline specification is re-estimated using reweighted observations, the magnitude, size and significance of the coefficients on the key variable of interest remains broadly unchanged (see Table 11).

If the BGPR variable captures the effects of other unobservable bank characteristics, then banks with different levels of BGPR might exhibit systematically different behaviour. As such, the regression could potentially deliver results similar to the baseline estimates even in periods that were relatively unaffected by geopolitical events. In addition, research has shown that difference-in-difference estimates can overstate the statistical significance of results and fail placebo tests in some circumstances (Bertrand et al., 2004). To address these concerns, we therefore run a placebo test, redefining the event period to a time when geopolitical shocks were more limited. Specifically, we set the *Pre* period from Q4 2019 to Q4 2020 and the *Post* period as starting in Q1 2021. This allows us to assess whether the observed effects of exposure to the Russian invasion of Ukraine are driven by pre-existing trends rather than the actual event.

The results in Table 12 show no significant impact of higher exposure when applying this placebo framework, reinforcing the validity of our baseline findings.[23]

5.2 Controlling for bank exposures to energy intensive sectors or firms

The Russian invasion of Ukraine resulted in a large increase in European energy prices as supplies of oil and gas to Europe were severely disrupted (Adolfsen et al., 2022; Gazzani et al., 2024). To ensure that our results are not driven by this energy shock, an extension of the baseline regression was run including a variable to control for the exposure of banks to highly energy-intensive sectors or firms prior to the war.

To do so, data from AnaCredit were merged with firm-level emissions data from Urgentem, which provide a measure of carbon intensity.[24] The exposure indicator weights the emissions of each firm by its share in the total loans granted by the bank. Emissions data are missing for some firms, and the resultant indicator is available for approximately 33% of the [total number of] loans in our initial sample.

To assess whether this information affects the key variable of interest, we include an additional interaction term between banks' exposure to emission-intensive firms and the Post dummy. Table 14 shows that banks' exposure to emission-intensive firms did not significantly influence the impact of the geopolitical risk shock, as the magnitude of the main coefficient remains comparable to the baseline. Furthermore, the interaction term is not statistically significant, suggesting that exposure to high-emitting firms did not

[23] In addition, we also redefine the event period to occur later in time. Specifically, we set the Post period from Q4 2021 to Q4 2023 and define the Post period as starting in Q1 2022 (see Table 13).

[24] Specifically, Scope 1, Scope 2, and Scope 3 emissions tons of CO2 equivalent (tCO2e) divided by revenue.

materially affect lending behaviour after the start of the invasion.

As a robustness test, an alternative sector-level indicator was computed to increase coverage. To do so, Eurostat data on emissions and energy use were normalised by sectoral gross value added (GVA). These sectoral intensity measures were then merged with information on the sectoral exposure of banks using loan portfolio data on the country and sector of the borrower. Finally, to construct a bank-level indicator, the sectoral energy of each borrower was weighted by its share in the total loans granted by the bank. The resultant variable was then interacted with the *Post* invasion dummy variable.

The results displayed in Table 15 suggest that adding the additional interaction variable of *Post* and the energy exposure of banks does not change the key findings with regard to geopolitical risk shock. The positive coefficient suggests that banks with higher exposure to energy-intensive firms or industries actually exhibited slightly higher lending than other banks, after controlling for their geopolitical exposure. At the same time, the coefficient on the key variable of interest, $BGPR \times Post$, remains similar to the baseline.

5.3 Potential sample selection bias due to including only firms with multiple bank relationships

As explained previously, in most of the above regression specifications, we control for heterogeneity in credit demand across firms by focusing on firms with multiple bank relationships, following the approach of Khwaja and Mian (2008). However, a limitation of this method is that it excludes single-bank relationships, as these are absorbed by the inclusion of borrower-time fixed effects. To test the robustness of our results, we replace the borrower-time fixed effects with ILS-time fixed effects, which allows us to include borrowers with single-bank relationships while still controlling for certain demand characteristics (Coulier et al., 2024; Degryse et al., 2019). The results, reported in Table

16, show that our findings are robust to the inclusion of single-bank relationship firms: the interaction term $BGPR \times Post$ remains negative and statistically significant. In addition, if we restrict the sample to firms borrowing from a single bank only (Table 17), the coefficient on the interaction of interest remains negative and significant even in the restricted sample.

5.4 Concerns about the potential confounding effect of the monetary policy tightening

The Russian invasion of Ukraine occurred in the first quarter of 2022, just before the start of the ECB monetary policy tightening cycle in mid-2022 (Burlon et al., 2025).This could raise concerns that the credit supply effects estimated in the regressions are the result of the heterogeneous effects on banks caused by the monetary policy tightening rather than geopolitical factors. However, a number of the features of the baseline specification, and the evolution of the estimated results over time, serve to allay these concerns. First, the baseline specification includes country-time fixed effects which should absorb country (euro area) invariant factors such as monetary policy. Also it is not clear why the effect of monetary policy should have an outsized effect on those banks with higher geopolitical risk exposure, as captured by the $BGPR$ index. Second, the timing of the first ECB interest rate hike occurred in July 2022, 5 months after the Russian invasion of Ukraine. However, to more accuratly address this concern, an alternative specification is run at monthly frequency (see Table 18). The monthly analysis runs using data for the period between 2021 M9 and 2022 M6. From this it is clear that there was already sizeable and statistically significant effects prior to the onset of ECB monetary policy tightening. Moreover, the baseline specification suggests that the estimated geopolitical effects did not persist throughout the monetary policy tightening cycle - the magnitude of the coefficients already appears to fade in Q4 2022 even if ECB rate increases continued until September 2023. Even without considering the potential lags at which monetary policy tightening may affect bank lending, this pattern seems inconsistent with the hypothesis that the estimates are capturing the effect of monetary policy rather than the geopoliticalrisk shock.

5.5 Concerns about the consistency of standard errors

The baseline specification utilises standard errors clustered at the bank-level to account for serial correlation within each bank. As a robustness test we also double-cluster at the time and bank level (see Table 19). In addition, following Bertrand et al. (2004), we also collapse the time series information into a single "pre"- and "post"-period (i.e. the mean of the 5 months before and the mean of the 5 months after the invasion) to address concerns that the standard errors could be inconsistent and overstate the statistical significance of the estimates, as well as avoiding potential serial correlation. In this specification, the dependent variable is the change in the outstanding volumes of loans before and after the invasion. The values for the control variables are their mean value in the 5 months prior to the invasion.

The results in Table 20 are robust to both the alternative clustering, and the collapsed "pre"- and "post"-period specification, delivering coefficients with a similar sign, significance and magnitude to the baseline in practically all specifications.

5.6 Differences in loan types, maturity and other characteristics

In the baseline specification, the total outstanding borrowing amount includes both fixed rate and floating rate loans. However, it might be anticipated that geopolitical shocks would only affect floating rate loans, the rates on which can be more readily adjusted. To address this concern, an alternative specification was implement including *borrower×time×interest rate type*. The results in Table 21 are robust to the inclusion of these alternative fixed effects.

Relatedly, one might expect the effect of the geopolitical shock to vary depending on the maturity of loans. Faced with heightened uncertainty, banks may seek to shorten the maturity of their loans and become reluctant to lend for longer periods. To investigate this hypothesis, loans are allocated to buckets based on the quartile of the maturity. Using this information, a specification was run that included $borrower \times time \times maturity$ fixed effects. Once again, the key results are robust to this alternative specification (see Table 22).

5.7 Firm-bank level controls for loan characteristics

The response of bank lending supply to geopolitical shocks could vary depending on the features and characteristics of the loans from banks to individual firms. To ensure that this is not driving the key results, an alternative specification was implemented including three variables to control for loan characteristics at the bank-firm level. First, a variable capturing the weighted average residual maturity of a firm's loans from a given bank is included. Firms that have loans with a longer maturity may be perceived as being more risky and therefore more sensitive to heightened geopolitical risk. Second, a dummy variable is included, that takes a value of 1 if any of a firm's loans are in default. Firms that have loans in default may be perceived as more risky. Third, a variable that captures the sum of the protection value of a firm's loans was included. Intuitively, for a given loan size, the larger the insured value of firms' loans, the less risky they are. The regression also includes interactions of these three variables with the $Post$ dummy variable.

The results in Table 23 show that including these additional control variables does not notably alter the size, sign or significance of the coefficients on the key variable of interest, $BGPR \times Post$. The coefficient on the $default\ status \times BGPR \times Post$ interaction term is statistically significant and negative, while that on the $insurance\ protection\ value \times BGPR \times Post$ of a firm's loans is positive. These results are both consistent with the hypothesis that banks became more sensitive to the risk characteristics of firms' loans after the invasion.

6 Conclusions

Geopolitical tensions typically lead to heightened uncertainty, which can negatively affect future growth prospects and financial stability. As a result, they are a key concern for policymakers, financial institutions, and banks.

This paper shows that geopolitical risk can have a significant impact on the supply of bank lending, with pronounced knock-on effects on businesses. The Russian invasion of Ukraine provided a stark illustration of how adverse geopolitical events can rapidly shift risk perceptions and increase uncertainty, leading banks to curtail lending. The euro area was particularly vulnerable due to its geographical proximity to the event making it an ideal laboratory to study these effects.

The paper provides several insights that are crucial to understand the channels and mechanisms through which geopolitical risk can affect banks and the firms reliant on them. Granular loan level data, combined with a well specified difference-in-difference estimation approach, allow our analysis to make causal inferences about the effects of geopolitical risk on bank lending. Banks with higher exposure to the increase in geopolitical risk stemming from the Russian invasion of Ukraine cut lending supply to non-financial corporations more than their peers both at the intensive and extensive margins, as these banks were also less likely to establish new lending relationships. The results suggest that the behaviour of the banks was driven by increased risk aversion in the face of increased uncertainty, as banks with higher exposure to geopolitical risk increased their loan impairments but did not record a deterioration of their asset quality. The effects on the supply of bank lending was mitigated in the case of banks with larger capital buffers, suggesting that robust capitalisation can mitigate the adverse effects of geopolitical events. Banks constrained lending supply more to sectors reliant on inputs from countries aligned with Russia, suggesting that banks were concerned by firms' supply chain vulnerabilities. Relatedly, larger banks, which typically have greater exposure to larger export oriented firms, cut lending more than smaller banks, which tend to serve smaller domestically oriented companies.

The effects on bank lending behaviour had real economic consequences. Firms reliant on banks with higher exposure to geopolitical risk were unable to substitute loans, as they could not compensate for the reduction in lending through other sources of bank financing. This led to real economic effects, as the contraction in the credit supply of banks with higher exposure had tangible consequences for euro area firms. Indeed, firms that were more exposed to these institutions reduced both investment and employment.

These findings have important implications for policy. We show that these risks compelled banks to adjust their lending practices, tightening credit conditions. Analysing these reactions provides valuable insights for policymakers to coordinate responses, such as targeted macroprudential measures or lending support programs, to mitigate the broader economic impact of geopolitical crises. Understanding these dynamics is crucial for assessing systemic risks and enhancing the resilience of the euro area banking sector.

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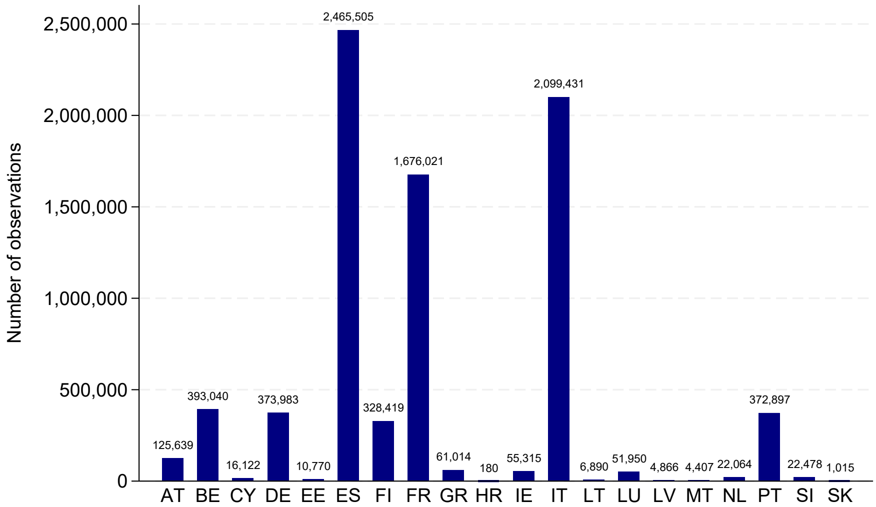
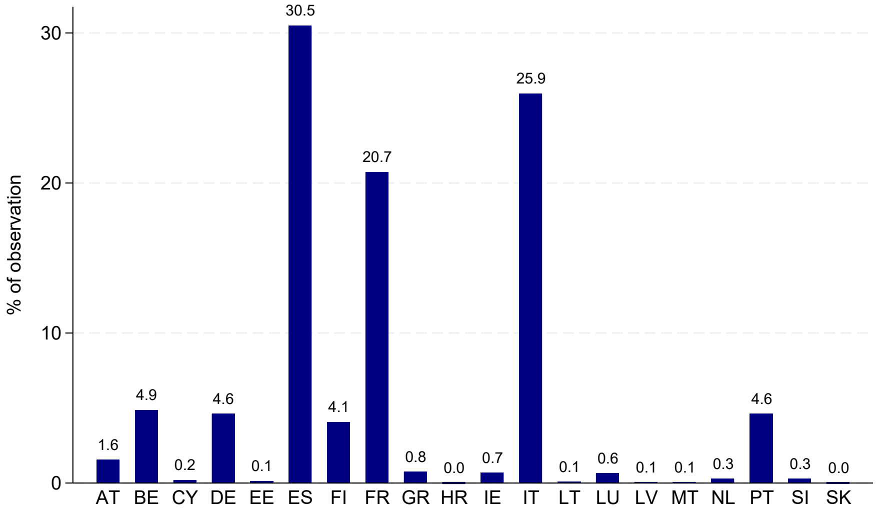
Tables and Figures

Figure 1: **Distribution of observations by country in the dataset**



Note: This figure represents the coverage per country of the number of observations after the merge of AnaCredit with supervisory bank-level data.



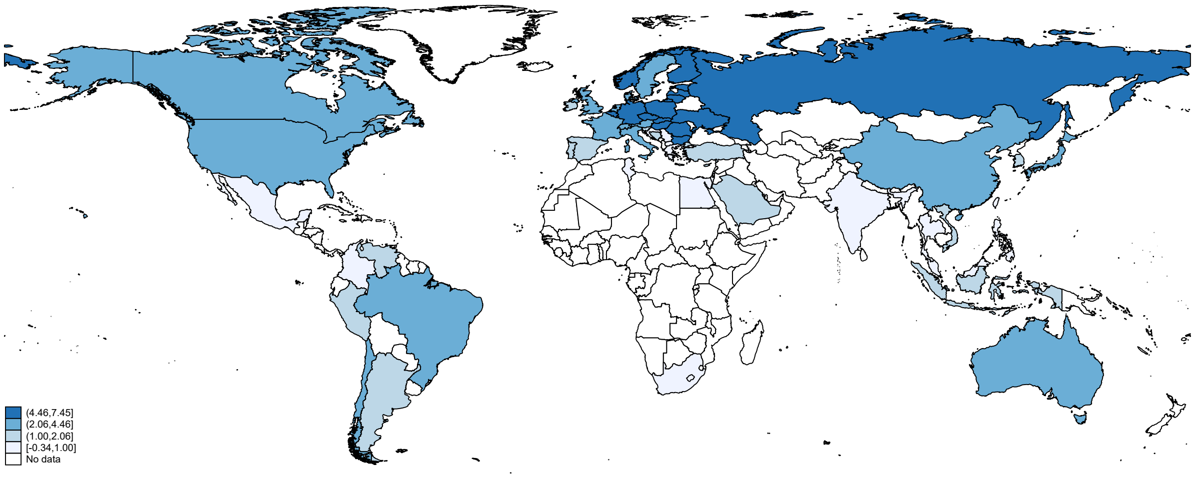
Note: This figure represents the the percentage of observations by country after the merge of AnaCredit with supervisory bank-level data.

Table 1: **Descriptive Statistics**

	N	Mean	Std.dev.	p25	p50	p75
Dependent variables						
Outstanding amount (euros)	7 240 328	868582.36	2157559	56201.29	165057.62	533159.00
Log outstanding amount	7 240 328	12.07	1.90	10.94	12.01	13.19
New loan (dummy)	7 240 328	0.05	0.22	0.00	0.00	0.00
New relationship (dummy)	19 197 283	0.17	0.37	0.00	0.00	0.00
Impairment amount (euros)	6 121 938	38633.60	3879747	89.00	477.00	2972.00
Log impairment amount	6 121 938	12.07	1.90	10.94	12.01	13.19
Days past due	7 228 011	32.47	202.67	0.00	0.00	0.00
Interest variable						
BGPR	7 240 328	3.24	0.90	2.20	3.51	3.80
Control variables - bank level						
Log total assets	7 240 328	5.41	1.62	4.37	5.55	6.74
Capital tier 1 ratio (%)	7 240 328	16.34	3.98	14.22	15.43	17.32
Deposit to liability ratio (%)	7 240 328	84.00	11.15	78.42	86.18	93.27
Return on asset	7 240 328	0.55	0.55	0.28	0.47	0.68
Cash to asset ratio (%)	7 240 328	14.69	5.63	11.61	14.63	17.66
Provision over loans	7 240 328	0.08	0.41	0.00	0.04	0.11
Distance to MDA (%)	7 204 803	2.43	5.13	0.00	0.85	2.85
Uninsured deposit ratio (%)	4 298 408	65.08	11.72	55.88	65.51	73.24
Emission intensive exposure	7 231 488	-0.08	0.30	-0.13	-0.05	0.08
Energy intensive exposure	7 240 328	-0.08	0.30	-0.13	-0.05	0.08
Control variables - loan level						
Log of weighted residual maturity	6 392 450	6.56	1.70	6.17	7.02	7.48
Default status	7 240 328	0.03	0.16	0.00	0.00	0.00
Log protection value	5 742 011	11.22	3.89	10.86	12.10	13.27
Firm variables						
Input dependencies (sectoral)	6 228 086	0.48	0.65	0.13	0.18	0.73
Exposed firm	14 921 687	0.12	0.32	0.00	0.00	0.00
Investment (change 2021-2022)	670 598	0.05	1.73	-0.03	-0.00	0.03
Log number of employees (change 2021-2022)	486 405	0.04	0.35	0.00	0.00	0.13
Log total assets (2021)	670 598	13.74	1.61	12.62	13.58	14.67
Cash to assets (2021)	670 598	0.17	0.22	0.03	0.10	0.25
Leverage	670 598	0.21	0.51	0.01	0.14	0.31
EBITDA	670 598	0.10	1.69	0.03	0.08	0.16
Ratio of tangible assets	670 598	0.30	0.30	0.05	0.20	0.48

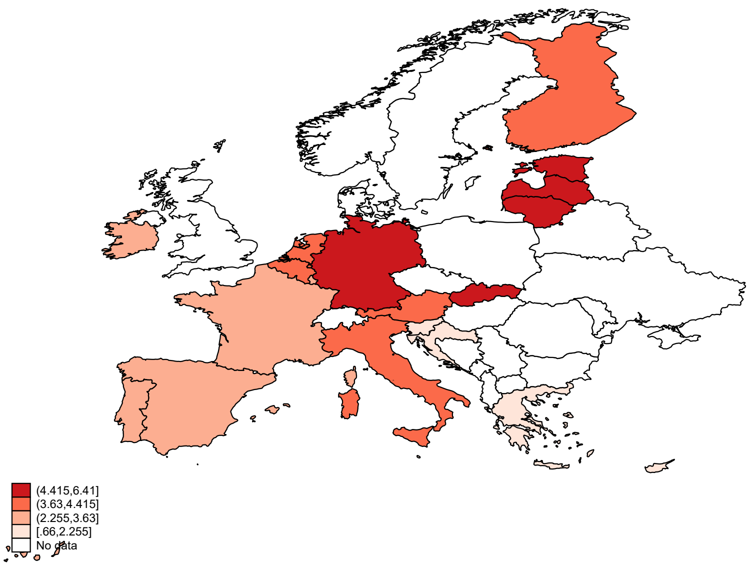
Note: Descriptive statistics cover the period from 2021Q1 to 2023Q1, unless otherwise specified

Figure 2: **Variation of the country level GPR z-scores around the invasion**



Note: The figure displays the variation of the country-level GPR z-scores between 2021 Q4 and 2022 Q1. Darker colours indicate a higher variation.

Figure 3: **Average Bank-level GeoPolitical Risk (BGPR) index by euro area country**



Note: The figure displays country-level aggregates, calculated as weighted averages of the BGPR of individual banks headquartered in each country included in our sample. The weights are based on each bank's share of total assets within its respective country. Darker colours indicate a higher exposure to geopolitical risk.

Figure 4: **Distribution of Bank-level GeoPolitical Risk (BGPR) index across the 363 banks in the sample**

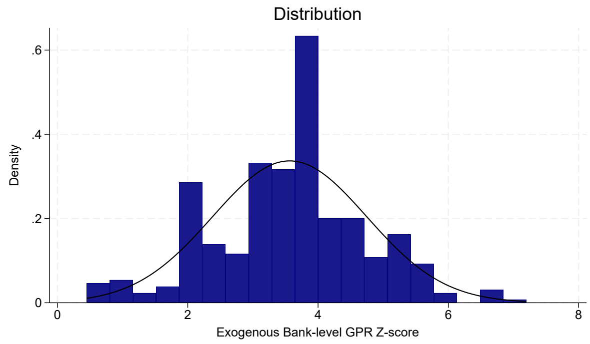
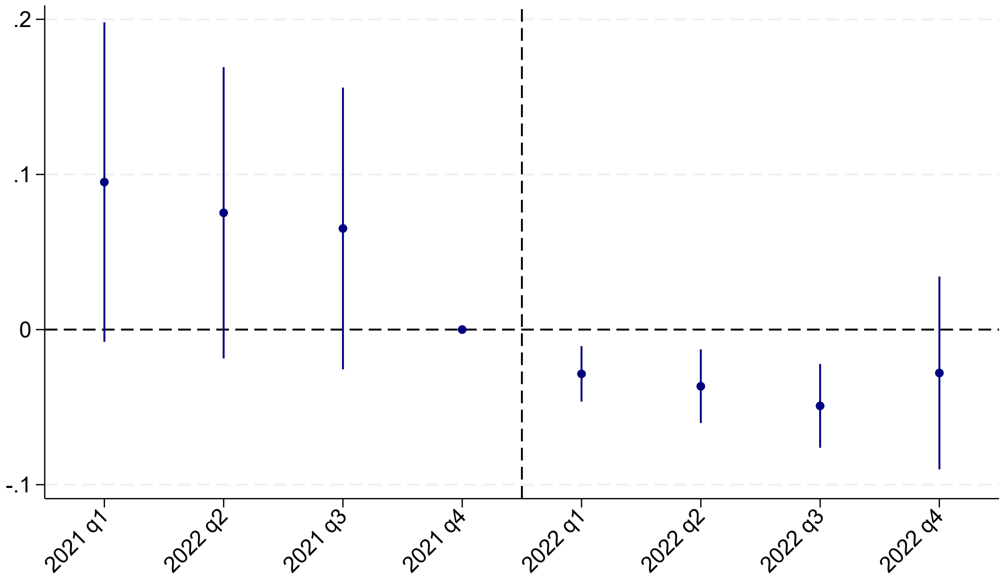


Table 2: **Effects on the intensive margin**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
BGPR_b	0.022				
	(0.163)				
$\text{BGPR}_b \times \text{Post}_t$	-0.066***	-0.078***	-0.071***	-0.083***	-0.092***
	(0.023)	(0.020)	(0.015)	(0.019)	(0.019)
L.size $(\log)_{b,t}$			0.149***	0.131**	0.132**
			(0.048)	(0.053)	(0.053)
L.size $(\log)_{b,t} \times \text{Post}_t$			-0.002	0.011*	0.012*
			(0.006)	(0.006)	(0.006)
L.capital tier1 $\text{ratio}_{b,t}$			0.006**	0.004	0.005*
			(0.003)	(0.003)	(0.003)
L.capital tier1 $\text{ratio}_{b,t} \times \text{Post}_t$			-0.001	-0.000	-0.001
			(0.001)	(0.001)	(0.001)
L.deposit-to-liability $\text{ratio}_{b,t}$			0.003	0.004	0.004
			(0.003)	(0.003)	(0.003)
L.deposit-to-liability $\text{ratio}_{b,t} \times \text{Post}_t$			-0.000	0.002**	0.002***
			(0.001)	(0.001)	(0.001)
$\text{L.ROA}_{b,t}$			-0.026***	-0.022***	-0.023***
			(0.005)	(0.008)	(0.008)
$\text{L.ROA}_{b,t} \times \text{Post}_t$			0.018**	0.016	0.016
			(0.008)	(0.013)	(0.013)
L.cash-to-asset $\text{ratio}_{b,t}$			-0.000	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
L.cash-to-asset $\text{ratio}_{b,t} \times \text{Post}_t$			-0.000	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
L.provisions-to-loans $\text{ratio}_{b,t}$			0.171	-0.359	-0.409
			(1.163)	(1.375)	(1.354)
L.provisions-to-loans $\text{ratio}_{b,t} \times \text{Post}_t$			0.388	1.245	1.404
			(1.440)	(1.682)	(1.647)
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	7,240,328	7,240,327	6,559,556	6,437,583	6,437,583
R^2	0.666	0.692	0.704	0.956	0.956

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Figure 5: **Estimated dynamic impact of an increase in BGPR on the intensive margin**



Note: The chart presents the estimated response of bank-firm loan amounts to a one-standard-deviation increase in bank-level geopolitical risk index following the Russian invasion of Ukraine at different time horizons with 2021 Q4 as reference period. The estimated model include borrower×time, borrower×bank and country×time fixed effects. Confidence intervals are set at the 99% level

Table 3: **Effects on the probability of extending a new relationship**

	Dependent variable: new relationship			
	(1)	(2)	(3)	(4)
$BGPR_b$	-0.040***			
	(0.014)			
$BGPR_b \times Post_t$	-0.039*	-0.038*	-0.056**	-0.061**
	(0.023)	(0.021)	(0.025)	(0.026)
Bank controls/interactions	✓	✓	✓	✓
ILS × Time FE	✓	✓	✓	✓
Bank FE		✓	✓	✓
Country × Time FE				✓
N	19 197 283	19 197 282	17 997 224	17 997 224
R^2	0.171	0.208	0.217	0.217

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 4: **Effects on impairment volumes**

	Dependent variable: log(impairments)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	-0.204				
	(0.171)				
$BGPR_b \times Post_b$	0.230**	0.263**	0.247***	0.227**	0.241**
	(0.108)	(0.109)	(0.089)	(0.092)	(0.098)
Bank controls/interactions			✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	6,121,938	6,121,936	5,618,863	5,510,484	5,510,484
R^2	0.794	0.821	0.824	0.944	0.944

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 5: **Effects on the number of days past due**

	Dependent variable: Days past due			
	(1)	(2)	(3)	(4)
$\text{BGPR}_b \times \text{Post}_b$	1.082	-0.299	0.539	-0.343
	(2.132)	(2.445)	(1.028)	(1.294)
Outstanding amount (log)	-2.442***	-2.991***	-1.015	-1.437*
	(0.887)	(0.966)	(0.690)	(0.786)
Bank controls/interactions		✓		✓
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
ILS FE			✓	✓
N	7,232,992	6,806,623	6,773,935	6,369,152
R^2	0.013	0.015	0.283	0.287

Significance levels are: * p < 0.10 ; ** p < 0.05 ; *** p < 0.01. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 6: **Amplifiers and mitigators : effects of bank characteristics**

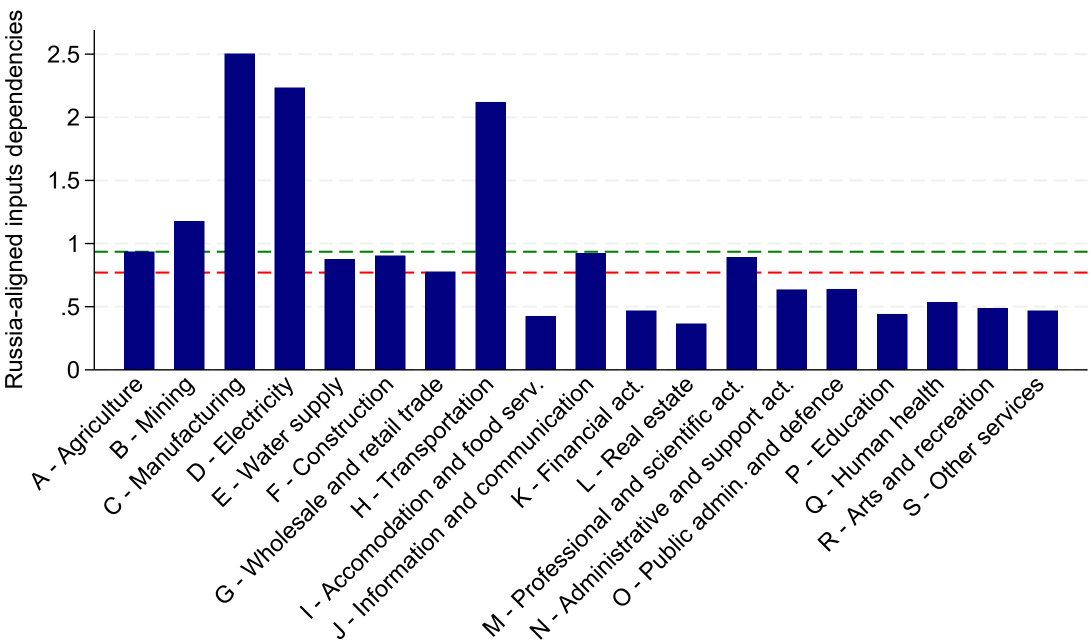
	Dependent variable: log(loan amount)			
	Cash to assets *continuous*	Distance to MDA *continuous*	Size *continuous*	Uninsured deposit ratio *continuous*
$\text{BGPR}_b \times \text{Post}_t$	-0.093***	-0.100***	0.000	-0.122
	(0.017)	(0.020)	(0.025)	(0.097)
$\text{BGPR}_b \times \text{Post}_t$	0.001	0.003*	-0.018***	0.000
$\times \text{Moderator}_f$	(0.105)	(0.001)	(0.006)	(0.002)
Bank controls/interactions	✓	✓	✓	✓
Double interaction included	✓	✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓
Borrower × Bank FE	✓	✓	✓	✓
Country × Time FE	✓	✓	✓	✓
N	7 212 500	7 162 947	7 212 500	6 699 981
R^2	0.952	0.942	0.952	0.948

Significance levels are: * p < 0.10 ; ** p < 0.05 ; *** p < 0.01. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 7: **List of Russia-Aligned Countries Based on UN Voting Patterns**

Country name		
Cambodia	Senegal	Antigua and Barbuda
Zimbabwe	Guinea	Chad
South Africa	Saint Lucia	Azerbaijan
Mali	Grenada	Rwanda
Afghanistan	Vietnam	Morocco
Kazakhstan	Comoros	Yemen
Ghana	Pakistan	Lesotho
Angola	Benin	Namibia
Madagascar	Bhutan	Tajikistan
Kyrgyzstan	Gambia	Mozambique
Russia		

Figure 6: **Average of sectoral ratio of inputs dependencies to Russia-aligned countries across euro area countries**



Note: The figure displays the country-level average of the measure of Russia-aligned input dependencies. The green dotted line represents the 75th percentile, and the red dotted line represents the 50th percentile.

Table 8: **Effects of being in a vulnerable sector**

	Dependent variable: log(loan amount)			
	Domestic		Euro-area	
	Top 25th	*Top 50th*	*Top 25th*	*Top 50th*
$\text{BGPR}_b \times \text{Post}_t$	-0.084***	-0.073***	-0.086***	-0.074***
	(0.017)	(0.014)	(0.017)	(0.014)
$\text{BGPR}_b \times \text{Post}_t$	-0.027***	-0.032**	-0.034***	-0.035**
$\times$ Vulnerable $\text{sector}_{c,f}$	(0.009)	(0.015)	(0.009)	(0.015)
Bank controls/interactions	✓	✓	✓	✓
Double interaction included	✓	✓	✓	✓
Borrower $\times$ Time FE	✓	✓	✓	✓
Borrower $\times$ Bank FE	✓	✓	✓	✓
Country $\times$ Time FE	✓	✓	✓	✓
N	6 228 086	6 228 086	6 360 359	6 360 359
R^2	0.955	0.955	0.955	0.955

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 9: **Substitution effect at firm level**

	Dependent variable: log(loan amount)		
	(1)	(2)	(3)
Exposed $\text{firm}_j \times \text{Post}_t$	-0.022***	-0.015***	-0.015***
	(0.008)	(0.005)	(0.005)
ILS $\times$ Time FE	✓	✓	✓
Weighted controls		✓	✓
Weighted controls$\times$post			✓
Firm FE	✓	✓	✓
N	2,116,256	1,699,591	1,699,591
r2	0.973	0.978	0.978

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at the largest lender level are reported in parentheses.

Table 10: **Firm real effects**

	Investment		Log(number of employees)	
Exposed firm$_j$	-0.083**	-0.086**	-0.006***	-0.006**
	(0.040)	(0.042)	(0.002)	(0.002)
Size (log)$_{i,2021}$	-0.030**	-0.030**	0.005***	0.006***
	(0.013)	(0.013)	(0.001)	(0.001)
Cash-to-assets$_{i,2021}$	-0.129***	-0.129***	-0.000	-0.001
	(0.025)	(0.025)	(0.006)	(0.006)
Debt-to-assets$_{i,2021}$	0.061	0.061	0.025***	0.026***
	(0.058)	(0.058)	(0.008)	(0.008)
EBITDA$_{i,2021}$	-0.037	-0.037	-0.022**	-0.022***
	(0.029)	(0.029)	(0.004)	(0.004)
Tangible asset ratio$_{i,2021}$	-0.048	-0.049	0.169***	0.169***
	(0.064)	(0.064)	(0.017)	(0.017)
Bank controls	✓		✓	
ILS FE	✓	✓	✓	✓
N	458,433	458,433	366,421	366,421
r2	0.094	0.094	0.172	0.173

Significance levels are: * p ¡ 0.10 ; ** p ¡ 0.05 ; *** p ¡ 0.01.

Table 11: **Covariate-rebalancing with generalised propensity score weighting**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
BGPR_b	0.075				
	(0.161)				
$\text{BGPR}_b \times \text{Post}_t$	-0.082***	-0.088***	-0.078***	-0.095***	-0.102***
	(0.024)	(0.021)	(0.015)	(0.018)	(0.018)
L.size $(\log)_{b,t}$			0.142***	0.157***	0.159***
			(0.042)	(0.050)	(0.050)
L.size $(\log)_{b,t} \times \text{Post}_t$			0.000	0.014*	0.016**
			(0.007)	(0.007)	(0.008)
L.capital tier1 $\text{ratio}_{b,t}$			0.007**	0.006**	0.007**
			(0.003)	(0.003)	(0.003)
L.capital tier1 $\text{ratio}_{b,t} \times \text{Post}_t$			-0.001	-0.000	-0.001
			(0.001)	(0.001)	(0.001)
L.deposit-to-liability $\text{ratio}_{b,t}$			0.004	0.005	0.005
			(0.003)	(0.003)	(0.003)
L.deposit-to-liability $\text{ratio}_{b,t} \times \text{Post}_t$			0.000	0.002**	0.002***
			(0.001)	(0.001)	(0.001)
$\text{L.ROA}_{b,t}$			-0.028***	-0.025***	-0.025***
			(0.005)	(0.007)	(0.007)
$\text{L.ROA}_{b,t} \times \text{Post}_t$			0.018**	0.015	0.016
			(0.008)	(0.012)	(0.012)
L.cash-to-asset $\text{ratio}_{b,t}$			0.000	-0.000	-0.000
			(0.001)	(0.001)	(0.001)
L.cash-to-asset $\text{ratio}_{b,t} \times \text{Post}_t$			-0.000	-0.001	-0.001
			(0.001)	(0.001)	(0.001)
L.provisions-to-loans $\text{ratio}_{b,t}$			0.011	0.007	0.006
			(0.018)	(0.021)	(0.020)
L.provisions-to-loans $\text{ratio}_{b,t} \times \text{Post}_t$			-0.002	0.005	0.007
			(0.020)	(0.023)	(0.023)
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	7,240,328	7,240,327	6,559,556	6,437,583	6,437,583
R^2	0.666	0.692	0.704	0.956	0.956

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 12: **Placebo test - one year before**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	0.041				
	(0.179)				
$BGPR_b \times Post_t$	-0.019	-0.011	-0.003	-0.011	-0.010
	(0.024)	(0.021)	(0.017)	(0.017)	(0.018)
Bank controls/interactions			✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	6 517 419	6 517 419	5 802 371	5 695 628	5 695 628
R^2	0.662	0.688	0.702	0.948	0.948

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 13: **Placebo test - one year after**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	-0.044				
	(0.150)				
$BGPR_b \times Post_t$	0.021	0.015	0.012	0.006	0.006
	(0.031)	(0.027)	(0.020)	(0.019)	(0.022)
Bank controls/interactions			✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	4 628 689	4 628 686	4 213 622	4 085 941	4 085 941
$R2^2$	0.670	0.696	0.708	0.966	0.966

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 14: **Control for exposure to emission intensive firms**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	0.024				
	(0.165)				
$BGPR_b \times Post_b$	-0.067***	-0.078***	-0.070***	-0.083***	-0.093***
	(0.022)	(0.021)	(0.015)	(0.019)	(0.020)
Firm emission intensive $Exposure_b$	0.038				
	(0.191)				
Firm emission intensive $Exposure_b$ $\times$ $Post_t$	0.011	-0.013	-0.010	-0.001	-0.005
	(0.029)	(0.025)	(0.020)	(0.023)	(0.024)
Bank controls/interactions			✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N N	7 231 488	7 231 488	6 551 984	6 437 360	6 437 360
R^2	0.666	0.692	0.704	0.956	0.956

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 15: **Control for exposure to energy intensive sectors**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	0.022				
	(0.164)				
$BGPR_b \times Post_b$	-0.070***	-0.079***	-0.071***	-0.085***	-0.093***
	(0.021)	(0.020)	(0.014)	(0.018)	(0.019)
Energy intensive $exposure_b$	0.015				
	(0.098)				
Energy intensive $exposure_b \times Post_t$	0.040**	0.024*	0.017*	0.027***	0.022**
	(0.017)	(0.013)	(0.009)	(0.009)	(0.010)
Bank controls/interactions			✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	7 231 606	7 231 605	6 552 043	6 437 420	6 437 420
R^2	0.666	0.692	0.704	0.956	0.956

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 16: **Effects on lending when including firms with single bank relationships**

	Dependent variable: log(loan amount)			
	(1)	(2)	(3)	(4)
$BGPR_b$	0.009			
	(0.110)			
$BGPR_b \times Post_t$	-0.056***	-0.062***	-0.053***	-0.058***
	(0.015)	(0.015)	(0.011)	(0.012)
Banks controls/interactions			✓	✓
ILS × Time FE	✓	✓	✓	✓
Bank FE		✓	✓	✓
Country × Time FE				✓
N	19 197 283	19 197 282	17 997 224	17 997 224
R^2	0.359	0.387	0.397	0.397

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 17: **Effects on lending with only firms with single bank relationships**

	Dependent variable: log(loan amount)			
	(1)	(2)	(3)	(4)
$BGPR_b$	0.027			
	(0.142)			
$BGPR_b \times Post_t$	-0.059***	-0.072***	-0.064***	-0.078***
	(0.022)	(0.020)	(0.014)	(0.012)
Banks controls/interactions			✓	✓
ILS × Time FE	✓	✓	✓	✓
Bank FE		✓	✓	✓
Country × Time FE				✓
N	6,780,644	6,780,643	6,150,914	6,038,573
R^2	0.436	0.468	0.485	0.488

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 18: **Monthly estimation, 2021 M9 - 2022 M6**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
BGPR_b	0.010				
	(0.157)				
$\text{BGPR}_b \times \text{Post}_t$	-0.043***	-0.049***	-0.054***	-0.047***	-0.053***
	(0.013)	(0.012)	(0.012)	(0.009)	(0.009)
Bank controls	✓	✓	✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	9 054 058	9 054 056	9 038 401	8 969 985	8 969 985
Number banks	356	355	352	351	351
R^2	0.667	0.695	0.694	0.962	0.962

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. Standard errors are reported in parentheses.

Table 19: **Clustering standard errors at bank and time level**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
BGPR_b	0.022				
	(0.082)				
$\text{BGPR}_b \times \text{Post}_t$	-0.066	-0.078***	-0.071***	-0.083***	-0.092***
	(0.111)	(0.015)	(0.015)	(0.016)	(0.018)
Banks controls/interactions	✓	✓	✓	✓	
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	7,240,328	7,240,327	6,559,556	6,437,583	6,437,583
R^2	0.666	0.692	0.704	0.956	0.956

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank- and time-level. Standard errors are reported in parentheses.

Table 20: **Collapse methodology on monthly data**

	Dependent variable: $\Delta log(loanamount)$	
	(1)	(2)
BGPR_b	-0.047***	-0.046***
	(0.002)	(0.002)
L.size (log)		0.009***
		(0.001)
L.capital tier1 ratio		0.001***
		(0.000)
L.deposit-to-liability ratio		0.001***
		(0.000)
L.ROA		-0.003
		(0.002)
L.cash-to-asset ratio		-0.001***
		(0.000)
L.provisions-to-loans ratio		0.919***
		(0.302)
Firm FE	✓	✓
N	3 361 490	3 332 557
R2	0.001	0.002

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are reported in parentheses.

Table 21: **Including interest rate fixed effects**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	0.152*				
	(0.083)				
$BGPR_b \times Post_t$	-0.046***	-0.055***	-0.046***	-0.063***	-0.070***
	(0.014)	(0.015)	(0.010)	(0.014)	(0.014)
Banks controls/interactions	✓	✓	✓	✓	
Borrower × Time × Interest rate type FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	3,498,923	3,498,922	3,191,792	3,032,110	3,032,110
R^2	0.777	0.788	0.796	0.978	0.978

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank- and time-level. Standard errors are reported in parentheses.

Table 22: **Including maturity rate fixed effects**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	0.142**				
	(0.071)				
$BGPR_b \times Post_t$	-0.067***	-0.068***	-0.059***	-0.059***	-0.066***
	(0.017)	(0.016)	(0.011)	(0.016)	(0.017)
Banks controls/interactions	✓	✓	✓	✓	
Borrower × Time × Maturity FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	2,995,651	2,995,647	2,775,294	2,644,314	2,644,314
R^2	0.810	0.824	0.828	0.985	0.985

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank- and time-level. Standard errors are reported in parentheses.

Table 23: **Adding loan level controls**

	Dependent variable: log(loan amount)				
	(1)	(2)	(3)	(4)	(5)
BGPR_b	0.163*				
	(0.093)				
$\text{BGPR}_b \times \text{Post}_t$	-0.064***	-0.052***	-0.042***	-0.060***	-0.063***
	(0.018)	(0.017)	(0.012)	(0.014)	(0.014)
Weighted residual maturity $(\log)_{b,i,t}$	0.230***	0.206***	0.203***	0.088***	0.088***
	(0.021)	(0.013)	(0.013)	(0.009)	(0.009)
Weighted residual maturity $(\log)_{b,i,t}$ $\times$ Post_t	0.006	-0.003	-0.005	0.008	0.008
	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)
Default $\text{status}_{b,i,t}$	-0.024	0.021	0.020	0.025***	0.025***
	(0.059)	(0.040)	(0.039)	(0.009)	(0.009)
Default $\text{status}_{b,i,t}$ $\times$ Post_t	-0.067	-0.033	-0.035	-0.036***	-0.036***
	(0.068)	(0.056)	(0.054)	(0.011)	(0.011)
Protection value $(\log)_{b,i,t}$	0.075***	0.103***	0.101***	0.074***	0.074***
	(0.023)	(0.025)	(0.025)	(0.024)	(0.023)
Protection value $(\log)_{b,i,t}$ $\times$ Post_t	0.004	0.004	0.006**	0.005***	0.005***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)
Banks controls/interactions	✓	✓	✓	✓	
Borrower × Time × Maturity FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	4,539,022	4,539,019	4,250,512	4,174,609	4,174,609
R^2	0.802	0.829	0.831	0.981	0.981

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank- and time-level. Standard errors are reported in parentheses.

Appendix

Variables definitions

Table A1: Definitions of variables and their sources

[htbp] **Variable**	**Label**	**Definition**	**Source**
Dependent variables:			
Loan amount	log(loan amount)	Logarithm of the outstanding amount of loans from bank b to firm i	AnaCredit
New relationship		Dummy variable equal to 1 if: a) at time t a new firm that did not have a relationship in the previous quarter enters the AnaCredit registry, and b) a firm that was in the sample in $t-1$ acquires a loan from a new bank. It equals 0 otherwise.	AnaCredit
New loan		Dummy variable equal to 1 when the outstanding credit volume in lending relationships increases between $t-1$ and t, and equal to 0 otherwise	AnaCredit
Impairment volumes	log(impairments)	Sum of loss allowances held against a loan at the bank-firm level on the reporting date, based on expected credit losses under international or national accounting standards	AnaCredit
Days past due	days past due	The average number of days past due at bank-firm level, average at bank-firm level weighted by the size of each loan. Past due being considered when the payment of interest and/or principal is not made on time.	AnaCredit
Interest variable:			
Bank-level Geopolitical Risk	BGPR	Indicator built by weighting the change in the standardised country-level geopolitical risk (CGPR) indices between 2021Q4 and 2022Q1 with bank-level average asset-side exposures to the different countries (average on 2021Q1-2021Q4)	Caldara and Iacoviello (2022); Dieckelmann et al. (2025) and ECB Supervisory statistics
Control variables - bank level:			
Size	size(log)	Logarithm of bank total assets	ECB Supervisory statistics

Capitalisation	capital tier1 ratio	The Tier 1 Capital Ratio is the ratio of a bank's core equity capital (Tier 1 capital) to its risk-weighted assets, in percent.	ECB Supervisory statistics
	distance to MDA	The CET1 ratio in excess of the maximum distributable amount, in percent.	ECB Supervisory statistics
Funding structure	deposit-to-liability ratio	Share of total liabilities funded by customer deposits, expressed, in percent.	ECB Supervisory statistics
Profitability	ROA	The ratio of net income to total assets	ECB Supervisory statistics
Liquidity	uninsured deposit ratio	Share of a bank's total deposits that are not covered by a deposit insurance scheme, in percent	ECB Supervisory statistics
Asset quality	provisions-to-loans ratio	Total loan loss provisions divided by the total outstanding loan amount.	ECB Supervisory statistics
Emission intensive exposure	emission intensive exposure	Emission intensity of each borrower was weighted by its share in the total loans granted by the bank, the measure is standardized.	Urgentem, ECB Supervisory statistics and AnaCredit
Energy intensive exposure	energy intensive exposure	Sectoral energy of each borrower weighted by its share in the total loans granted by the bank, the measure is standardised.	Eurostat, ECB Supervisory statistics and AnaCredit
Control variables - loan level:			
Maturity	weighted residual maturity (log)	The logarithm of the residual maturity at bank-firm level, average at bank-firm level weighted by the size of each loan	AnaCredit
Default status	default status	Dummy variable that takes a value of 1 if any of a firm's loans with the bank are in default	AnaCredit
Protection value	protection value (log)	The logarithm of the sum residual maturity at bank-firm level	AnaCredit

Firm variables:			
Input dependencies	input dependencies	Computed at country sector (Nace Rev.2) level, correspond to the share of Russian-aligned inputs over total inputs	Figaro - Eurostat
Exposed firm	exposed firm	Dummy taking the value of 1 if least 75% of the firm's loans were sourced from banks within the top 25th percentile of geopolitical risk exposure	AnaCredit, ECB Supervisory statistics
Investment	investment	Change between 2021 and 2022 in the ratio of fixed assets to total assets	Orbis
Number of employees	nb. of employees	Change between 2021 and 2022 in the logarithm of number of employees	Orbis
Size	size(log)	Logarithm of bank total assets	Orbis
Liquidity	cash-to-assets	The ratio of cash including to total assets	Orbis
Leverage	debt-to-assets	The ratio of debt over total assets	Orbis
Profitability	EBITDA	Ratio of Earnings before interest, taxes, depreciation, and amortization over total assets	Orbis
Tangible assets	tangible asset ratio	The ratio of of tangible assets over total assets	Orbis

Probability of extending a new loan

As an alternative to the extensive margin, Table A2 reports the results of regressions similar to the baseline, but now with the probability of a bank extending a new loan as the dependent variable. The results indicate that a one standard deviation increase in BGPR significantly reduces the probability of extending a new loan in an existing lending relationship by 1.2 percentage points.

Table A2: **Effects on the probability of issuing a new loan**

	Dependent variable: new loan				
	(1)	(2)	(3)	(4)	(5)
$BGPR_b$	-0.012				
	(0.007)				
$BGPR_b \times Post_t$	-0.011***	-0.012***	-0.012***	-0.011***	-0.012***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Bank controls/interactions	✓	✓	✓	✓	✓
Borrower × Time FE	✓	✓	✓	✓	✓
Bank FE		✓	✓		
Borrower × Bank FE				✓	✓
Country × Time FE					✓
N	7 240 328	7 240 327	6 559 556	6 437 583	6 437 583
R^2	0.462	0.471	0.475	0.675	0.675

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level. T-statistics are reported in parenthesis.

Bank-level analysis over longer period 2015q1 to 2024q3

To test whether our findings hold more broadly, we also investigate the relationship between geopolitical risk and bank lending at a bank level (rather than at the bank-firm level) over a longer period of time, i.e., between 2015Q1 and 2024Q3. Rather than focusing specifically on the Russian invasion of Ukraine, this analysis employs a panel setting with bank controls and different sets of fixed effects, using the following regression specification:

$$y_{b,t} = \beta_1 BGPR_{b,t-1} + \beta_2 X_{b,t-1} + \mu_b + \delta_t + \gamma_{c,t} + \varepsilon_{b,t} \tag{8}$$

where the dependent variable $y_{b,t}$ is the logarithm of the total outstanding amount of lending to non-financial corporates. The key variable of interest is $BGPR_{b,t-1}$ which is the lagged time-varying BGPR. Unlike the baseline specification, which focuses on the variation in the GPR between the quarters immediately before and after the invasion, the key variable of interest here is $BGPR_{b,t-1}$ which is the level of the BGPR for bank b at each point in time $t-1$ over the entire sample period.[25]

$X_{b,t-1}$ is the same set of lagged bank controls used in the baseline specification. This alternative specification also includes a number of fixed effects, specifically, μ_b controls for time-invariant bank fixed effects, δ_t denotes a vector of time fixed effects, while $\gamma_{c,t}$ controls for country×time effects.

The results indicate that a one standard deviation rise in the BGPR (i.e. 1.18) is associated on average with a decline of 7.67% in the banks' loan amount to NFCs. Thus, these results are consistent with those of the baseline regression, albeit, in this setting we cannot determine if this relationship is causal.

[25] This analysis uses the bank-level geopolitical risk index as introduced by (Dieckelmann et al., 2025).

Table A3: **Bank level - loans non-financial corporations**

	Dependent variable: log(loans to NFCs)			
	(1)	(2)	(3)	(4)
L.BGPR$_{b,t}$	-0.011	-0.076*	-0.062*	-0.062**
	(0.014)	(0.043)	(0.036)	(0.031)
L.size (log)$_{b,t}$			0.989***	0.989***
			(0.174)	(0.076)
L.capital tier1 ratio$_{b,t}$			-0.001	-0.001***
			(0.001)	(0.000)
L.deposit-to-liability ratio$_{b,t}$			0.009	0.009***
			(0.007)	(0.003)
L.ROA$_{b,t}$			0.018	0.018*
			(0.017)	(0.010)
L.cash-to-asset ratio$_{b,t}$			-0.009***	-0.009***
			(0.003)	(0.002)
L.provisions-to-loans ratio$_{b,t}$			-0.396	-0.396
			(0.388)	(0.356)
Bank FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Country × Time FE		✓	✓	✓
Double cluster standard errors				✓
N	11,939	11,934	11,406	11,406
R^2	0.943	0.948	0.955	0.955

Significance levels are: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are clustered at bank-level (except column (4) double clustered bank-time). T-statistics are reported in parenthesis.

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