The European Journal of Finance

ISSN: 1351-847X (Print) 1466-4364 (Online) Journal homepage: www.tandfonline.com/journals/rejf20

Does geopolitical risk affect bank lending behavior? Evidence from Europe

Laura Chiaramonte, Federico Mecchia, Andrea Paltrinieri & Stefano Piserà

THE EUROPEAN JOURNAL OF FINANCE
2025, VOL. 31, NO. 16, 2089–2113
https://doi.org/10.1080/1351847X.2025.2585959

Does geopolitical risk affect bank lending behavior? Evidence from Europe

Laura Chiaramonte[a], Federico Mecchia[b], Andrea Paltrinieri[c] and Stefano Piserà[d]

[a]Department of Management, University of Verona, Verona, Italy; [b]Department of Economics and Statistics, University of Udine, Udine, Italy; [c]Department of Economics and Business Management Sciences, Catholic University of Sacred Heart, Milan, Italy; [d]Department of Economics, University of Genoa, Genova, Italy

ABSTRACT

This paper investigates the impact of geopolitical risk (GPR) on bank credit growth by utilizing quarterly data from banks between 2008Q1 and 2023Q4 in 18 European countries. The main variable of interest is the GPR index developed by Caldara and Iacoviello (2022), which assesses risk at a country-specific level. We find that GPR leads to a decline in total lending, which is attributed to foreign activities, while no significant impact on domestic lending is documented. Our results also show a more resilient lending behavior in response to geopolitical shocks from state-owned banks compared with private banks, implying that the response of bank total lending to GPR is contingent on bank ownership structure. Moreover, as expected, the recent Russian invasion of Ukraine has amplified the negative effect of GPR on total lending, especially for those banks operating in countries located closer to Ukraine and Russia, and those that are more dependent on Russian gas. Finally, we find that the credit behavior of large and listed banks is unaffected by GPR, as are those countries with higher values of gross domestic product, those belonging to the eurozone, and those with low economic policy uncertainty, thus lending activity in these countries continues.

ARTICLE HISTORY
Received 13 January 2025
Accepted 13 October 2025

KEYWORDS
Geopolitical risk; bank lending; domestic and foreign loans; Russia–Ukraine invasion; European banks

JEL CLASSIFICATIONS
G21; G28; D81

1. Introduction

The most recent years have witnessed a number of dramatic events, ranging from terrorist attacks to actual wars and conflicts. The European context, in fact, has been the unlucky setting for a series of terrorist attacks carried out in Paris (2015), Brussels (2016), and Germany (2020). In addition, other parts of the world have also witnessed disastrous events, including the US–China trade war (2018), as well as the Russia–Ukraine (2022) and Israel (late 2023) conflicts.

The frequency with which these adverse geopolitical events have occurred in recent years, as well as the extent to which they have affected global dynamics, has focused the attention of policymakers, regulators, and academic researchers on geopolitical risk (GPR). As defined by Caldara and Iacoviello (2022), GPR is the risk associated with adverse events such as wars, terrorism, diplomatic friction, and any other event affecting 'the peaceful course of international relations.' A direct consequence of this definition is thus the independence of GPR, by its nature, from any business cycles; a fact that, together with its non-economic origin,[1] sets GPR apart from other sources of systematic risk, such as stock market volatility and economic policy uncertainty (EPU).

Given the prominent role GPR has acquired over recent years, assessing and understanding its impact on the economic-financial system as a whole, with particular attention reserved for the behavior of banks, thus proves to be of crucial importance (Dieckelmann et al. 2024). As we explain in Section 2, GPR can affect the banking sector via two main channels, namely the economic channel and the financial channel (Catalan et al. 2023;

CONTACT Laura Chiaramonte laura.chiaramonte@univr.it

Dieckelmann et al. 2024). Given the close connection between the real economy and the financial sector, GPR thus also influences various aspects of the banking system (such as funding, lending, solvency, asset quality, and profitability). Therefore, considering the lack of literature on the topic, the aim of our work is to shed some light on the impact of GPR on bank lending. In addition to the main analysis, we also investigate additional aspects to gain important insights regarding the different dynamics considered, including, for example, disaggregation in foreign and domestic loans, the role of ownership structure in determining the lending response of banks against fluctuations in GPR, and an assessment of the impact of proximity to Russia and Ukraine.

This paper provides several contributions to the literature. First, we contribute to understanding the implications of GPR on European bank lending by using the novel GPR index developed by Caldara and Iacoviello (2022) at a country-specific level. As explained in Section 3, the GPR measure is based on articles published in leading newspapers that discuss geopolitical frictions, and that capture 'real-time geopolitical tensions as perceived by the press, the public, global investors, and policymakers' (Caldara and Iacoviello 2022). This proves to be an additional contribution since the existing literature is based mainly on the use of the EPU index of Baker, Bloom, and Davis (2016; see Bordo, Duca, and Koch (2016); Chi and Li (2017); Hu and Gong (2019); Danisman, Ersan, and Demir (2020), among others). The only exception is Demir and Danisman (2021), who considered both indicators (GPR and EPU) in analyzing their impact on credit growth. However, GPR differs from other macroeconomic uncertainty indicators for several reasons[2] (see Phan, Tran, and Iyke 2022), and can subsequently result in a different outcome with regard to banking behavior. This was shown by Demir and Danisman (2021), who found that economic uncertainty reduces overall bank credit growth in emerging economies, but GPR does not.

Our second contribution relates to the geographical coverage of the sample banks. To the best of our knowledge, it is the first study to explain whether and how GPR affects the credit activity of individual banks in Europe. Recent trade tensions, such as Russia's war in Ukraine, have increased stock market volatility (Piserà et al. 2024) and have thus deeply affected many European countries, which are consequently more exposed to the GPR emanating from these turbulent events.

Third, given that the types of credit more directly affected by all geopolitical tensions are bank loans classified by geographical location (domestic versus foreign), and that this distinction has been neglected by previous studies, we also aim to fill this research gap. Therefore, for the first time, apart from the main analysis of the full sample focused on total lending, as an additional analysis of those sample banks for which data are available, we disaggregate the total lending of each bank in a domestic versus foreign context.

Moreover, we also contribute to the related literature by verifying whether ownership structure can play a role in determining the lending response of banks against the fluctuations in GPR. To do this, we interact the GPR target variable with a dummy variable that considers whether the bank is public (state owned) or private.

A further contribution derives from the long period considered (2008Q1–2023Q4), which allows us to take into consideration the recent Russian invasion of Ukraine (i.e. the European geopolitical event with the highest recorded peak for the GPR index developed by Caldara and Iacoviello (2022)), to verify its impact on the relationship between GPR and bank lending, as well as the role that a country's proximity to Ukraine and Russia, or dependence on Russian gas, could play.

Finally, by adopting a heterogeneous cross-country sample of European banks, we further contribute by exploring whether some bank-specific characteristics, as well as different operating environment features, interact with GPR when the credit growth decisions of banks are shaped.

The main results of the empirical analysis can be summarized as follows. We find that total bank lending is negatively affected by geopolitical threats. Indeed, the increased uncertainty associated with geopolitical tensions prompts banks to contract lending supply to the economy, possibly because of an increase in the credit risk of customers and/or the spread of negative investor sentiments that determine a decrease in credit demand. Therefore, our findings show that European banks tend to decrease the supply of total lending as GPR increases. Moreover, through additional analyses, we find that an increase in GPR has no effect on domestic lending and a negative impact on foreign lending. These results suggest that banks decrease foreign loans, may be because, owing to their nature, they are more exposed to geopolitical tensions, with potentially significant consequences for international trade finance, which could be curtailed.

Additionally, with regard to ownership structure, we find that in response to geopolitical shocks, state-owned banks display more resilient lending behavior than private banks. This shows that the effect of GPR on bank total lending is contingent on bank ownership structure.

Next, focusing on the impact of the most recent acute geopolitical event (i.e. the recent Russian invasion of Ukraine) on the GPR–bank lending linkage, by means of an interaction term, we also take into consideration, first, the role that a country's proximity to Ukraine and Russia could play, and second, a country's dependence on Russian gas. As expected, the recent Russian invasion of Ukraine has amplified the negative effect of GPR on total lending, especially for those banks operating in countries located closer to Ukraine and Russia, or those that are more dependent on Russian gas.

Finally, we find that the effect of GPR on total bank lending depends on the bank characteristics as well as the operating environment features. More specifically, we find that the credit behavior of large and listed banks is unaffected by GPR, as are those countries with higher values of gross domestic product (GDP), those belonging to the eurozone, and those with low EPU, thus lending activity continues. Throughout our work, we also employ alternative measures for GPR, as well as the Heckman two-step regression to validate our results.

The findings of the analysis are of particular interest to both regulators and policymakers since they provide some evidence of the impact on the real economy of potential structural changes in bank lending behavior in response to GPR. Therefore, our results provide a better understanding of how geopolitical events might ripple through the financial system, allowing for possible policy responses in advance. Moreover, they suggest that, in future, it is important for European banks to pay more attention to their GPR management procedures to mitigate the impacts on their financial statements, since these impacts can indirectly negatively affect activity in the real economy.

The rest of the paper is structured as follows. Section 2 provides an overview of the existing literature on the topic. Section 3 describes the data and methodology employed in the study. The main results are discussed in Section 4. Additional analyses and robustness checks are presented in Sections 5 and 6, respectively. Finally, Section 7 concludes the paper and provides policy implications.

2. Literature review

The adverse geopolitical events of the most recent years, such as the terrorist attacks in Paris (2015), Brussels (2016), and Germany (2020), and the US–China trade war (2018), as well as the recent Russia–Ukraine (2022) and Israel (late 2023) conflicts, have urged policymakers, regulators, and academic researchers to carefully consider GPR. Therefore, in light of the increasing relevance of GPR, especially recently, an urgent need exists to understand its impact on the economic-financial system as a whole, with a specific focus on bank behavior (Dieckelmann et al. 2024). Indeed, as shown in Figure 1, the banking sector can be exposed to GPR through two different, but strictly interconnected, channels – one economic and the other financial (Catalan et al. 2023; Dieckelmann et al. 2024).

More specifically, on the real economy side, adverse geopolitical events tend to increase uncertainty, causing a deterioration in investor and consumer sentiment that weighs on economic growth. In addition, international trade could also be curtailed since confidence is affected, or trade restrictions and sanctions are increased. Further, disruptions to global supply chains and commodity markets may again have a negative impact on economic growth, generating, for example, inflationary pressures. On the financial side, geopolitical tensions can affect capital flows and asset prices, among other things, and lead to volatility in commodity markets, exchange rates, stock prices, interest rates, and credit spreads. As stated by Banerjee, Sensoy, and Goodell (2024), close interactions exist between GPR and financial markets and, in fact, GPR is able to act as a risk transmitter, proving to be an enlarger of cross-market spillovers. Additionally, Choi and Havel (2025) concluded that there is a negative relationship between GPR and US investment in foreign bonds and equities, but that this happens only in emerging markets. Moreover, according to Feng et al. (2023), a negative relationship can be found between the capital flows of advanced and emerging economies, and increasing GPR, but this effect is greater for emerging countries.

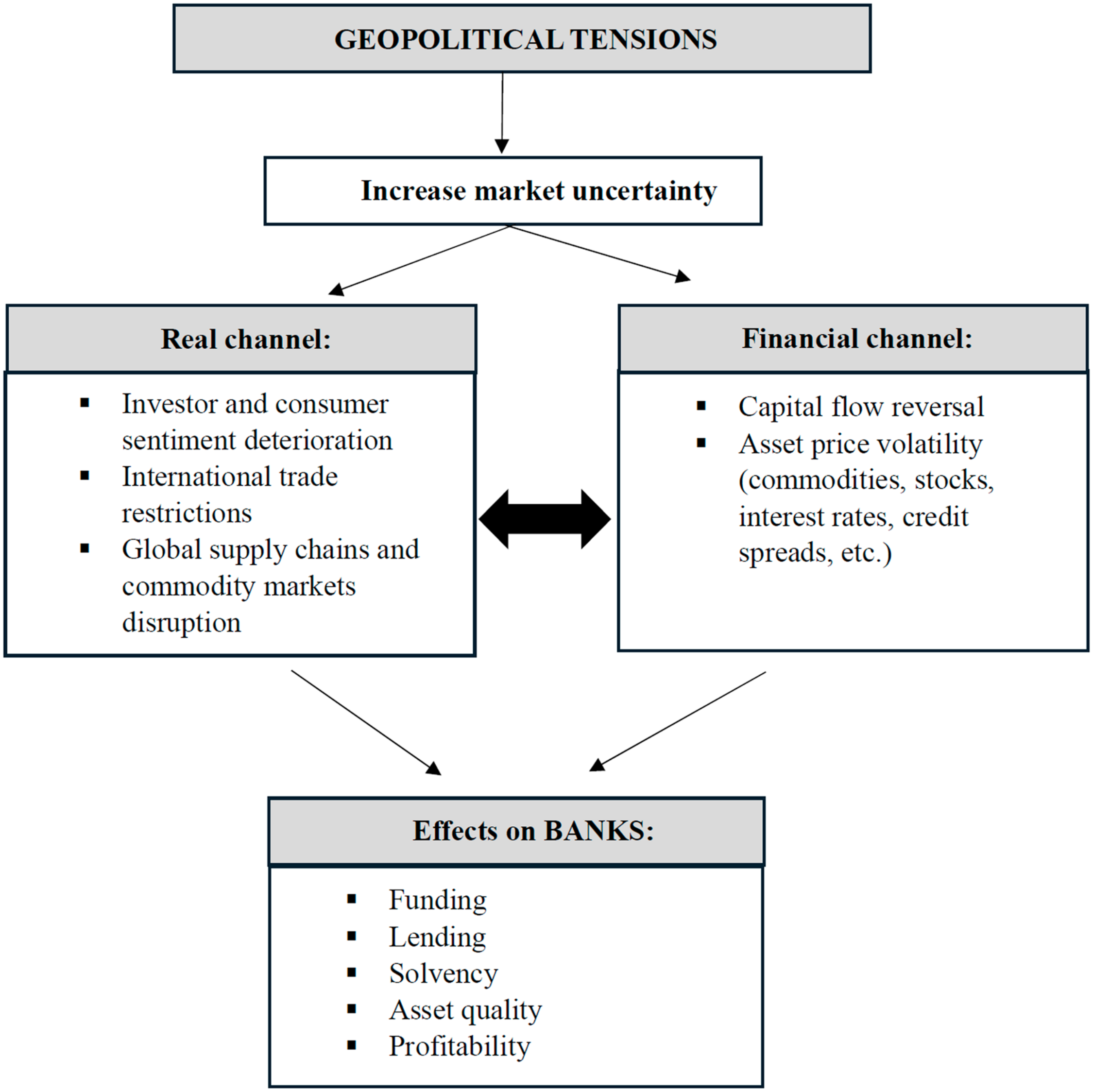

Figure 1. Key transmission channels of geopolitical tensions to banking sector. The figure shows the two key channels of transmission, financial and real, through which geopolitical tensions could affect the banking sector. Source: authors' elaboration.

Given the linkages between the real economy and financial sectors, feedback processes may reinforce direct effects. These adverse effects on the real economy and financial markets can have negative consequences for funding, lending, solvency, asset quality, and the profitability of banks.[3]

Although GPR can have significant impacts on banks, it has so far been largely a marginal consideration in the risk management activities of banks and in bank supervision, but may now need to become a focus. Indeed, only recently, European bank supervisors have acknowledged the significance of GPR for their future strategy and priorities (Enria 2022).

In recent years, various authors have addressed the issue of GPR from the perspective of firms and especially from the perspective of banking. In this regard, Wang, Wu, and Xu (2024) focused their attention on firm-level corporate investment and consequently determined that GPR has a negative effect on this type of investment. From the perspective of banking, Trinh and Tran (2024) analyzed the effect of GPR on the financial stability of global banking systems, concluding that the former has detrimental consequences on the latter. Moreover, Shabir et al. (2023), after having determined that economic and geopolitical uncertainty have detrimental effects on bank risk, observed that these negative consequences can be reduced through the power of the CEO and strong boards. In addition, Behn, Lang, and Reghezza (2025) determined that there is a non-linear interconnectedness between GPR and bank solvency, with almost unsignificant effects for moderate positive changes in GPR and a decrease in bank capitalization in cases where high levels of GPR are reached. Further, through their analysis, Wang, Song, and Lu (2025) found that systemic risk is increased by GPR through the rising effect of the latter on bank risk and bank assets, as well as the consequences for asset price bubble bursts. With regard to bank loans, Nguyen and Thuy (2023) analyzed the interconnectedness between GPR and the cost of bank loans, thus determining that higher loan prices are a consequence of GPR. Moreover, Nguyen and Thuy (2024) also concluded that GPR causes a reduction in the share of bank wholesale funding.

Despite the recent spark in the number of publications focusing on GPR and bank lending, the recent attention itself reserved for the issue of GPR justifies the existing evidence on how this type of risk affects the banking industry is limited and still unclear, particularly with regard to bank lending. To the best of our knowledge, to date, only two empirical studies have investigated the potential impact of GPR on credit availability, both finding mixed results. Demir and Danisman (2021), focusing on banks in emerging markets over the 2010–2019 period, found that credit growth is not affected by GPR. However, when they considered its impact on loan types, they observed that an increase in GPR hampers the growth of consumer and mortgage loans, but corporate loan growth is immune to GPR. Conversely, prior to Demir and Danisman (2021), Zhou et al. (2020) was the only study that focused on the GPR–bank lending relationship, but they used macro-level data for measuring credit growth. They documented that a rise in GPR lowered the level of domestic credit to the private sector in emerging markets over the 1985–2018 period.

Given the relatively scant and mixed empirical evidence in the related literature, limited to studies on emerging countries only, and the consequent stimulus to further investigate the impact of GPR on bank lending, especially after more frequently emerging geopolitical threats, we aim to shed light on the effect of GPR on the credit growth of individual banks by focusing on European banks and using an extensive dataset based on quarterly data over a long period (2008Q1–2023Q4). We expect that banks may respond to GPR by decreasing lending. More specifically, both credit supply and credit demand may be dampened by adverse macroeconomic developments caused by GPR (Dieckelmann et al. 2024). On the credit supply side, an increase in uncertainty leads to rising information asymmetry, making it difficult for banks to differentiate between good and bad borrowers, and thus making them less willing to lend to customers (Ashraf and Shen 2019; Phan, Tran, and Iyke 2022). On the credit demand side, customers may be reluctant to take out loans or invest in times of elevated uncertainty. Therefore, overall, we hypothesize a negative relationship: an increase in GPR should negatively affect the lending supply of individual banks.

Hp: An increase in geopolitical risk negatively affects bank lending.

3. Data and methodology

3.1. Sample description

We focus our analysis on Europe owing to its particular relevance. Recent trade tensions, such as those resulting from Russia's war in Ukraine, have amply underlined that many countries in this area are strategically vulnerable and could likely be increasingly exposed to GPR arising from the less peaceful course of international relations. Moreover, we concentrate our attention on banks headquartered in European countries to ensure consistency in regulatory environments, data availability, and responsiveness to domestic GPR. Although foreign banks operating through subsidiaries or branches may also influence credit supply, such as US banks active in Europe, their lending decisions often reflect group-level strategies rather than local risk perceptions. Thus, our analysis focuses on banks headquartered in those European countries (18 in total)[4] for which the recent GPR index developed by Caldara and Iacoviello (2022; i.e. our target variable) is available at a country-specific level.[5] The construction of this proxy for GPR is based on the number of geopolitical tension–related words that appeared in 10 of the foremost international newspapers. The GPR index is measured as the number of articles linked to GPR in each newspaper for each month relative to the total number of news articles. Further details regarding the GPR data are provided in the following section.

Next, from the S&P Capital IQ Database (formerly the SNL Financial Database), we collect consolidated balance sheet and financial statement data at the bank-period level to determine both our dependent variable (i.e. credit growth) and control variables, which are based on accounting data to control for credit supply in our empirical analysis. Our chosen period level is quarterly. The choice to use quarterly balance sheet data (rather than annual data) allows us to measure the impact on bank lending more accurately.

Finally, we collect data on macroeconomic control variables to control for the credit demand side from the Organisation for Economic Co-operation and Development (OECD) database. Table 1 provides a description of the variables used in the empirical analysis and the data sources.

We consider a relatively long period spanning from 2008Q1 to 2023Q4. This allows us to take into consideration a time frame characterized by several crucial geopolitical events that affected Europe, such as terrorist attacks in Paris in 2015, in Brussels in 2016, and in Germany in 2020, as well as the recent Russia–Ukraine conflict, which began in 2022 (i.e. the most acute geopolitical event ever in Europe and still ongoing).

After matching the datasets, the final sample is composed of 799 banks from 18 European countries, of which 457 belong to the geographical area of Northern and Eastern Europe, and 342 belong to the geographical area of Southern and Western Europe plus Turkey.

3.2. Measurement of geopolitical risk

GPR is the threat, realization, and escalation of adverse events associated with wars, terrorism, and tensions among states and political actors that affect the peaceful course of international relations (Dieckelmann et al. 2024; Salisu, Lasisi, and Tchankam 2022). This definition is consistent with the GPR index developed by Caldara and Iacoviello (2022), and it is the one used in our paper. Higher values for the GPR index suggest an increase in the likelihood or intensity of adverse geopolitical events, and vice versa.

More specifically, Caldara and Iacoviello developed two indexes: (i) the benchmark index GPR, which starts in 1985 and is available with daily frequency, using 10 newspapers,[6] by counting the number of newspaper articles related to adverse geopolitical events as a share of the total number of newspaper articles at a monthly frequency; and (ii) the GPR historical index (GPRH), which is based on the same methodology (an automated text search in the electronic archives of specific newspapers, counting the number of articles relating to adverse geopolitical events in each newspaper in each month with respect to the total number of news articles) but uses three newspapers,[7] starting in 1900 at a monthly frequency. For both indexes, the search is organized in eight categories: War Threats (Category 1), Peace Threats (Category 2), Military Buildups (Category 3), Nuclear Threats (Category 4), Terror Threats (Category 5), Beginning of War (Category 6), Escalation of War (Category 7), and Terror Acts (Category 8).

These two indexes are measured at a global level. Apart from these, Caldara and Iacoviello also developed two country-specific indexes inherent to GPR, namely country-specific GPRC and GPRHC, which were created following a similar procedure. Indeed, the two country-specific indexes were constructed by taking into consideration the share of articles that mention GPR as well as the country that is being discussed.[8] Data on the GPR indexes computed at the country level (GPRC and GPRHC) are available for 44 advanced and emerging countries, of which 18 are European countries, and these are the ones we focused on.[9]

For our empirical analyses, we collect data on the two country-specific GPR indexes (GPRC and GPRHC) for the 18 European countries over the 2008Q1–2023Q4 period with daily frequency, then adjust to that of all other variables used in the paper and observed with quarterly frequency.[10] Next, given that GPRC is measured based on consideration of a larger number of newspapers than GPRHC, we use GPRC in the main analysis and GPRHC in the robustness tests (see Section 5). Moreover, since GPRC is highly skewed, we use its natural logarithm (LN_GPRC), which is normally distributed (Fiorillo et al. 2023; 2024; Mertzanis and Tebourbi 2025).

Focusing on the trend of the annual average values of LN_GPRC for all 18 European countries considered over the 2008Q1–2023Q4 period, Figure 2 illustrates that the index observed shows a trend of constant growth, exhibiting significant variation and peaks around the start of the Russian invasion of Ukraine at the beginning of

Table 1. Definitions of variables.

Variable	Label	Definition	Source
Dependent variables			
Bank's total loans growth rate	LN_LOANS_GR	The natural logarithm of bank's total loans to customers at time t over t-1 (i.e. the previous quarter).	S&P Capital IQ database
Target variable			
Country-specific geopolitical risk	LN_GPRC	The natural logarithm of the country-specific geopolitical risk at time t (see Section 3.2 for further details).	Caldara and Iacoviello (2022)
Control variables			
Credit supply factors based on accounting data:			
Bank size	SIZE	The natural logarithm of bank total assets.	S&P Capital IQ database
Bank capitalization	ETA	The equity over total assets.	
Bank efficiency	CIR	Cost-to-income ratio.	
Bank credit portfolio quality	NPL_GL	The non-performing loans over gross loans.	
Bank liquidity	LA_TA	Liquid asset over total assets.	
Bank deposits funding	DEP_TA	Customer deposits over total assets.	
Bank profitability	ROAA	Return on average assets.	
Credit demand factors based on macroeconomic data:			
Country economic growth	GDPC	The quarterly percentage change in gross domestic product at country level.	OECD database
Country inflation	INFC	The quarterly inflation growth rate at country level.	
Other variables used in additional or robustness analyses			
Bank's domestic loan growth rate	LN_DOM_LOANS_GR	The natural logarithm of bank's domestic loans to customers at time t over t-1 (i.e. the previous quarter).	S&P Capital IQ database
Bank's foreign loan growth rate	LN_FOREIGN_LOANS_GR	The natural logarithm of bank's foreign loans to customers at time t over t-1 (i.e. the previous quarter).	
Alternative proxy for GPR	LN_GPRHC	The natural logarithm of the country-specific historical geopolitical risk at time t (see Section 3.2 for further details).	Caldara and Iacoviello (2022)
	LN_GPR_GT	The natural logarithm of the global geopolitical risk index determined using data collected by searching for the keyword 'geopolitical risk' in the Google Trends database.	Google Trends database
Dummy Russia–Ukraine conflict	D_RU_UA_conflict	Equals 1 for the 2022Q1–2023Q4 period; and 0 otherwise.	Own calculation
Dummy country's geographical proximity to Russia/Ukraine	D_RU_UA_proximity	Equals 1 for those European countries closer to Russia and Ukraine, and for which Caldara and Iacoviello (2022) provided data on GPR at the country level (Finland, Hungary, and Poland), and 0 otherwise.	Own calculation
Dummy country's dependence on Russian gas	D_RUgas	Equals 1 for those European countries more dependent on Russian gas in the years around the conflict (data provided by Eurostat), and for which Caldara and Iacoviello (2022) provided data on GPR at the country level (Finland, Germany, Hungary, Italy, Netherlands, Poland), and 0 otherwise.	Own calculation
Dummy ECB unconventional liquidity injections	D_UNC_LIQ_INJ	Equals 1 for the 2011Q4–2023Q4 period, in which the European Central Bank (ECB) provided liquidity to eurozone banking systems through the unconventional liquidity injections long-term refinancing operations (LTROs) and targeted long-term refinancing operations (TLTROs), and 0 otherwise.	Own calculation

(*continued*).

Table 1. Continued.

Variable	Label	Definition	Source
Dummy public	D_public	Equals 1 for bank public ownership, and 0 otherwise. This information is collected by the S&P Capital IQ database.	Own calculation
Economic policy uncertainty index	EPU	The country-specific EPU index developed by Baker, Bloom, and Davis (2016), which refers to uncertainty regarding economic policies such as monetary, fiscal, or regulatory policy.	Baker, Bloom, and Davis (2016)
Proxy for fintech	Mobile_pay	The country-specific total payments made by mobile phones to pay bills.	World Bank's Global Financial Inclusion Database (Findex)

This table provides a description of all the variables used in our analyses and the source of the data used to collect them.

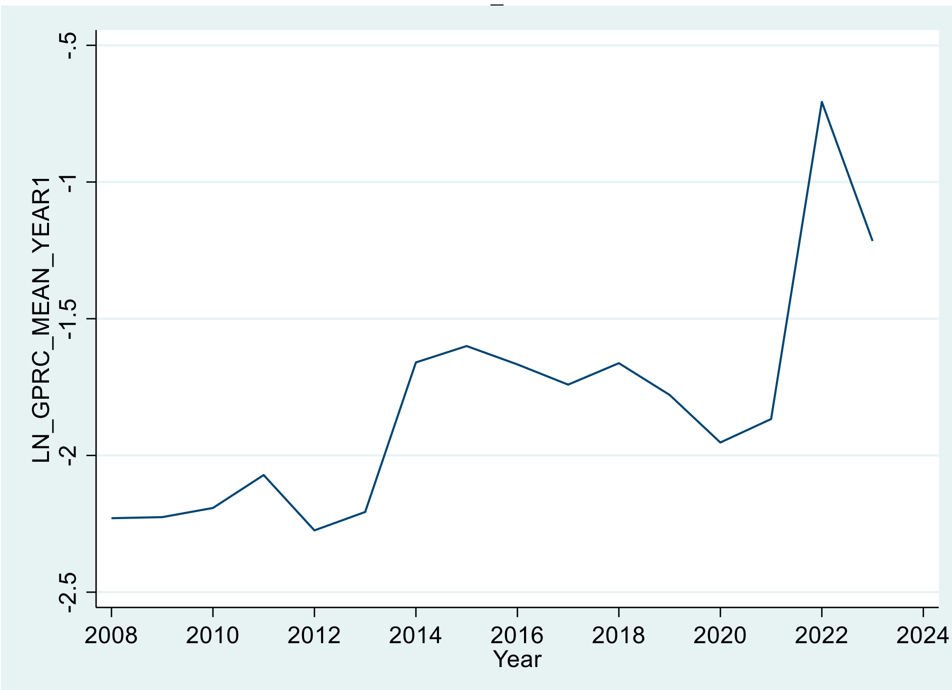

Figure 2. Geopolitical risk (GPR) index trend for the 18 European countries considered. This figure shows the trend of the annual average values of the GPR index at the country-specific level (GRPC), in terms of the natural logarithm (LN_GPRC) developed by Caldara and Iacoviello (2022) and relative to the 18 European countries for which GPR data are available, over the 2008Q1–2023Q4 period. Source: authors' calculation on data available at https://www.matteoiacoviello.com/gpr_country.htm.

2022. Moreover, the indicator exhibits other highs corresponding with further adverse events that have affected European countries, such as the terroristic attacks in Paris in 2015, in Brussels in 2016, and in Germany in 2020.

Examining any potential differences in term of exposure to GPR among the 18 European countries considered in the same sample period, Figure 3 shows that, as expected, Russia (RU) and Ukraine (UA) register the largest GPR index values as a direct consequence of their ongoing conflict. In addition, Poland (PL) displays a high level of GPR, which is likely due to its proximity to Russia and Ukraine. High values of GPR are also recorded by Germany (DE), France (FR), and the United Kingdom (UK), likely caused by the various terrorist attacks that occurred in Europe over the past approximately 10 years.

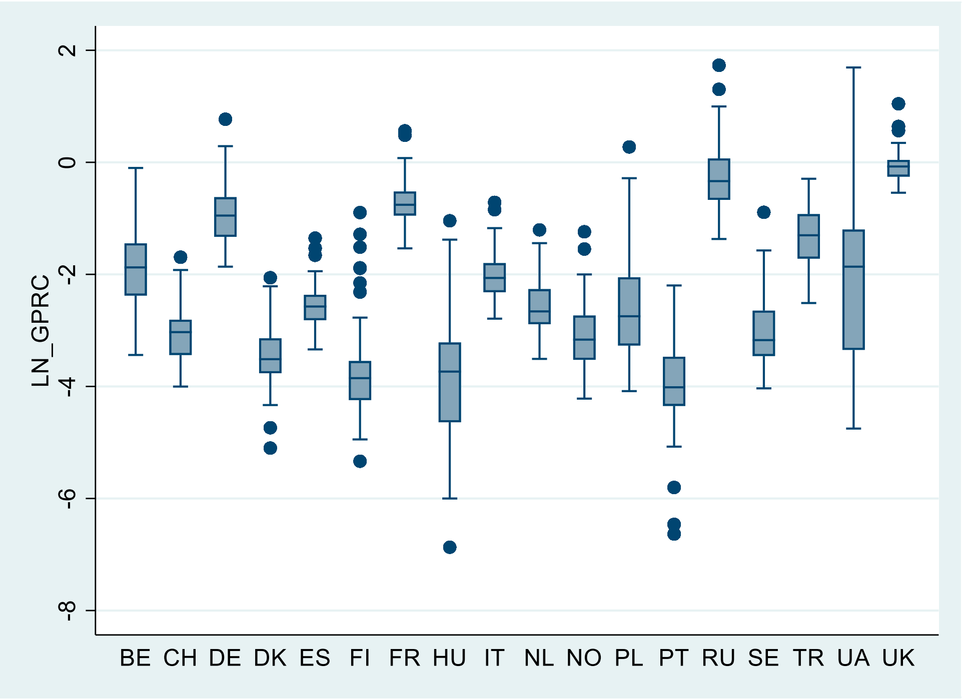

Figure 3. Distribution of the GPR index by country. This figure shows the distribution of the GPR index at country-specific level (GPRC), in terms of natural logarithm (LN_GPRC) developed by Caldara and Iacoviello (2022), in each 18 European countries considered in our analysis, over the 2008Q1–2023Q4 period. Source: authors' calculation on data available at https://www.matteoiacoviello.com/gpr_country.htm.

3.3. Empirical methodology

To study the relationship between GPRC and bank lending, we estimate the following specification:[11]

$$\begin{aligned} LN\_LOANS\_GR_{i,t} = {} & \beta_1(LN\_GPRC)_{i,t-1} + \beta_2(SIZE)_{i,t-1} + \beta_3(ETA)_{i,t-1} + \beta_4(CIR)_{i,t-1} + \beta_5(NPL\_GL)_{i,t-1} \\ & + \beta_6(LA\_TA)_{i,t-1} + \beta_7(DEP\_TA)_{i,t-1}\ \beta_8(ROAA)_{i,t-1} + \beta_9(GDPC)_{c,t-1} \\ & + \beta_{10}\ (INFLATION)_{c,t-1} + \delta_i + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where i refers to the bank, t indicates the quarter, c refers to the country, δ_i $\delta_i\delta_i$is bank fixed-effects (FE), and $\epsilon_{i,t}$ represents the standard errors clustered by the bank. As an alternative model specification, we also perform the model using quarter FE.[12] We run the empirical analyses over a relatively long period spanning from 2008Q1 to 2023Q4.

Our dependent variable is the loan growth rate ($LN\_LOANS\_GR_{i,t}$). We measure this as the natural logarithm of total loans to customers at time t over t-1 (i.e. the previous quarter). Figure 4 shows the trend of the annual average value of the total loan growth rate of our European sample banks over the 2008Q1–2023Q4 period. Following a substantial decrease in 2008 as a result of the global financial crisis, the annual lending growth rate did not return to pre-crisis levels, first owing to the sovereign debt crisis (2010–2014), and then because of the COVID-19 pandemic (2020–2021), as illustrated in Figure 4.

Our target variable is LN_GPRC, which is the natural logarithm of the GPR calculated in each quarter for each of the 18 European countries for which Caldara and Iacoviello provided data (as discussed in Section 3.2).

In our empirical analysis, we also aim to account for both demand and supply of credit (see Table 1). To control for credit supply, following the related literature (see Carlson, Shan, and Warusawitharana 2013; Del Giovane, Eramo, and Nobili 2011; Kapan and Minoiu 2013, among others), we include a set of control variables based on accounting data collected by the S&P Capital IQ Database. To proxy for bank size (SIZE), we use the natural

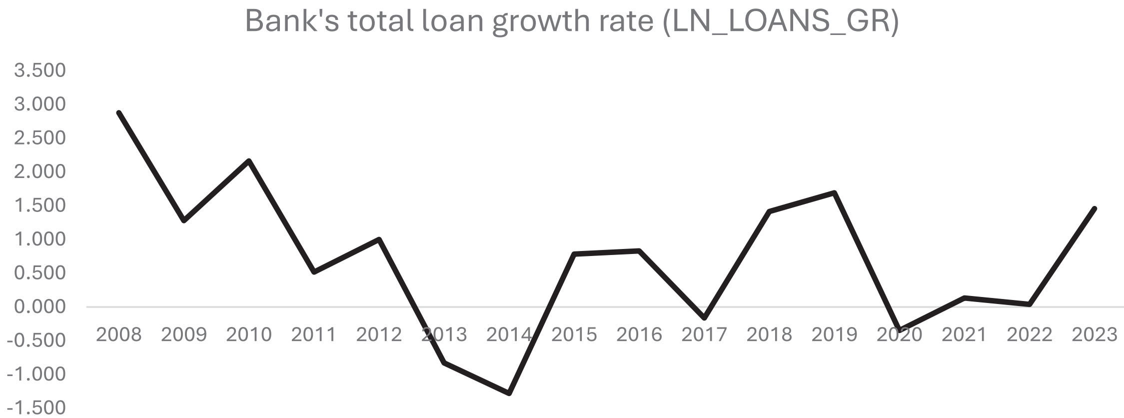

Figure 4. Lending trend of our sample European banks. This figure shows the trend of the annual average value of the total loan growth rate of our sample banks (belonging to the 18 European countries for which the GPR index, developed by Caldara and Iacoviello, is available) over the 2008Q1–2023Q4 period. This variable is computed as the natural logarithm of the bank's total loans to customers at time t over t-1 (i.e. the previous quarter). See Table 1 for details.

Table 2. Summary statistics of control variables.

Variables	Mean	Std. Dev.	Min.–Max.
Credit supply factors based on accounting data:			
SIZE	14.796	2.433	7.704–21.832
ETA	12.291	10.120	0.772–66.389
CIR	60.511	26.932	11.627–195.366
NPL_GL	7.398	12.178	0–74.662
LA_TA	32.258	20.825	2.857–94.616
DEP_TA	60.283	22.803	0–93,539
ROAA	0.845	2.212	−0.813–9.878
Credit demand factors based on macroeconomic data:			
GDPC	0.266	1.545	−6.584–6.869
INFC	3.493	3.902	−1.103–17.333

This table reports the summary statistics of the control variables of our sample banks from 18 European countries over the 2008Q1–2023Q4 period. See Table 1 for a description of these variables. All covariates based on the accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail.

logarithm of a bank's total assets. We measure bank capital as equity to total assets (ETA). Next, we include the cost-to-income ratio (CIR) as a proxy for bank operational efficiency. We employ the ratio of non-performing loans to gross loans (NPL_GL) as a proxy for credit risk. As proxy for bank liquidity, we use the ratio of liquid assets to total assets (LA_TA). Moreover, given that banks often rely on deposit funding to allocate credits, we also use the customer deposits to total assets ratio (DEP_TA).[13] To account for bank earnings, we consider the return on average assets (ROAA).[14]

To control for changes in credit demand owing to macroeconomic conditions, for each country considered, we include these variables based on macroeconomic data: the quarterly percentage change in gross domestic product (GDPC), and the quarterly inflation growth rate (INFC). Both were collected from the OECD database.

To account for potential endogeneity problems, all the explanatory variables used in our analyses are lagged by one-quarter compared with the dependent variable. Moreover, all covariates based on accounting data not measured as natural logarithms are winsorized at 1 percent of each tail.[15]

Table 2 displays the descriptive statistics of the aforementioned control variables over the 2008Q1–2023Q4 period. The data emphasizes that SIZE has a mean of 14.796 and a standard deviation of 2.433. Bank capitalization (ETA) is on average equal to 12 percent, but considering the minimum and maximum values, it can be seen

Table 3. Baseline model: Total lending.

	Total loans (LN_TOT_LOANS_GR)	
Variables	(I)	(II)
LN_GPRC (−1)	−1.217*	−1.716**
	(0.624)	(0.799)
SIZE (−1)	−2.859*	−1.846
	(1.678)	(2.006)
ETA (−1)	−0.170	−0.086
	(0.716)	(0.711)
CIR (−1)	0.000	−0.013
	(0.021)	(0.021)
NPL_GL (−1)	−0.236	−0.236
	(0.164)	(0.165)
LA_TA (−1)	0.284*	0.269*
	(0.162)	(0.156)
DEP_TA (−1)	−0.089	−0.071
	(0.183)	(0.198)
ROAA (−1)	0.186	0.195
	(0.492)	(0.491)
GDPC (−1)	0.040	0.532**
	(0.117)	(0.239)
INFC (−1)	−0.052	0.101
	(0.150)	(0.167)
Bank FE	Yes	Yes
Quarter FE	No	Yes
Cluster SE bank	Yes	Yes
N. of. obs.	9.494	9.494
R-squared	0.059	0.097

This table presents the results of the estimation of panel regressions for our sample banks from the 18 European countries for which the recent GPR index, developed by Caldara and Iacoviello (2022; i.e. our target variable), is available at the country-specific level. The period observed spans from 2008Q1 to 2023Q4. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank fixed-effects (FE) are included in all models. In model (II), we also control for quarter FE. Clustered standard errors by the banks are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

that there are some banks with a very high capitalization ratio (66.389 percent) and others with a very low capitalization ratio (0.772 percent). In terms of operational efficiency, the CIR spans from 11.627 per cent to 195.366 percent, revealing a wide variation. However, on average, European banks show good cost efficiency, with a CIR of approximately 60 percent. The quality of the credit portfolio, on average, shows a low level of NPLs (7.398 percent of NPL_GL), although some banks that continued to have high levels of NPLs in their balance sheet (74.662 percent as maximum value). There are also significant differences among our sample banks with regard to the liquidity ratio. The variable LA_TA spans from 2.857 percent to 94.616 percent, showing a wide variation. The average value of DEP_TA is equal to 60 percent, revealing that banks tend to finance themselves mainly through customer deposits. In terms of profitability, although the sample average is positive (0.845 percent), some banks show negative values for ROAA (−0.813 percent as a minimum value).

In terms of macroeconomic variables, our descriptive statistics show that the growth in GDP is, on average, equal to 0.266 percent, while the inflation rate during the period under investigation is, on average, equal to 3.493 percent. Moreover, Table 2 shows that the variation in the inflation rate is more than double that of GDP growth (3.902 percent for INFC versus 1.545 percent for GDPC).

Table 4. Additional analysis: Accounting for the geographical location of bank lending.

Variables	Domestic loans (LN_DOM_LOANS_GR)	Foreign loans (LN_FOREIGN_LOANS_GR)
LN_GPRC (−1)	0.313	−3.108***
	(0.462)	(1.237)
Control variables (−1)	Yes	Yes
Bank FE	Yes	Yes
Quarter FE	Yes	Yes
Cluster SE bank	Yes	Yes
N. of. obs.	5.677	3.506
R-squared	0.051	0.157

This table presents the results of the estimation of panel regressions for our sample banks from 18 European countries for which data on domestic and foreign loans (collected by S&P Capital IQ database) are available. The period observed spans from 2008Q1 to 2023Q4. The dependent variables, used alternatively in Equation (1), are the natural logarithm of the quarterly growth rate of domestic customer loans (LN_DOM_LOANS_GR) and the natural logarithm of the quarterly growth rate of foreign customer loans (LN_FOREIGN_LOANS_GR). As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank and quarter fixed-effects (FE) are included in all models. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

4. Main results

Table 3 shows the results of our baseline panel regressions for total loans to customers over the 2008Q1–2023Q4 period. In column (I), the specification includes only bank FE, while in column (II), the specification includes bank and quarter FE. The dependent variable is the change in natural logarithm (stock) of credit granted by bank *i* at time *t* (quarter).

As hypothesized, we find a negative and significant relationship between our target variable LN_GPRC (i.e. the proxy for GPR at the country level developed by Caldara and Iacoviello (2022)) and the dependent variable LN_LOANS_GR. This means that geopolitical tensions tend to decrease the total credit growth of European banks. More specifically, we find that with an increase of 1 percent of GPRC, total lending decreases by 1,217 percent (in Model I) and by 1,716 percent (in Model II), with potential implications for customer access to credit. This implies that, on the credit supply side, greater uncertainty, as a consequence of an increase in geopolitical tensions, tends to lead to rising information asymmetry, making it difficult for banks to differentiate between good and bad borrowers, thus becoming less willing to lend to customers (Ashraf and Shen 2019; Phan, Tran, and Iyke 2022). On the credit demand side, customers may be reluctant to take out loans or invest in times of elevated uncertainty. Therefore, in both cases, an increase in GPR leads to a negative impact on the lending activity of individual banks. Our results do not support the findings of Demir and Danisman (2021), who found no effect of GPR on total credit growth, although their focus was only on sample banks in emerging countries.

Focusing on the other variables that can affect total lending, Table 3 shows that, among the credit supply variables based on accounting data, SIZE and LA_TA play a significant role in explaining credit growth during the period observed. With reference to SIZE, smaller banks seem to lend more, perhaps owing to the so-called ‘relationship lending phenomenon’. Moreover, we find a positive relationship between LA_TA and LN_LOANS_GR, suggesting that the banks that are more liquid seem to be lending more. Thus, bank liquidity is needed to sustain bank lending (Carletti, Goldstein, and Leonello 2020; Vives 2014).

With regard to the credit demand variables based on macroeconomic data, only GDPC is significant, showing a positive relationship with total bank lending, as expected. As countries worsen their GDP growth rate, credit demand decreases.

Table 5. Additional analysis: The role of bank ownership structure.

	Total loans (LN_TOT_LOANS_GR)	
Variables	(I)	(II)
LN_GPRC (−1)	−2.988***	−3.537***
	(0.670)	(0.827)
D_public	26.854	16.460
	(40.885)	(43.299)
D_public∗LN_GPRC (−1)	4.117***	3.953***
	(1.116)	(1.071)
Control variables (−1)	Yes	Yes
Bank FE	Yes	Yes
Quarter FE	No	Yes
Cluster SE bank	Yes	Yes
N. of. obs.	9.494	9.494
R-squared	0.061	0.098

This table presents the results of the estimation of panel regressions for our sample banks from the 18 European countries for which the recent GPR index, developed by Caldara and Iacoviello (2022), i.e. our target variable LN_GPRC, is available at the country-specific level, taking into account the role of bank ownership structure. Thus, our target variables are the LN_GPRC; the dummy public (D_public), which equals 1 for bank public ownership, and 0 otherwise; and their interaction. The information on bank ownership structure is collected by the S&P Capital IQ database. The period observed spans from 2008Q1 to 2023Q4. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank fixed-effects (FE) are included in all models. In model (II), we also control for quarter FE. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

5. Additional analyses

5.1. Accounting for geographical location of bank lending

Given that the type of credit that could be more directly affected by geopolitical tensions are bank loans classified by geographical location (domestic versus foreign), and since this distinction has been neglected by previous related papers (with the exception of Zhou et al. (2020), who focused only on domestic loans to the private sector, but at a macro level), we also aim to fill this gap. Therefore, as an additional analysis, for those sample banks for which data are available, we disaggregate the total lending of each bank in domestic versus foreign locations. The dependent variables, used alternatively in Equation (1), are the natural logarithm of the quarterly growth rate of domestic customer loans (LN_DOM_LOANS_GR) and the natural logarithm of the quarterly growth rate of foreign customer loans (LN_FOREIGN_LOANS_GR). Table 4 shows the results obtained, including both bank and quarter FE, over the 2008Q1–2023Q4 period.

Unlike Zhou et al. (2020), who focused only on domestic credit to the private sector and showed the negative impact of GPR, we find that an increase in GPR has no effect on domestic lending. Moreover, also concentrating for the first time on the impact of GPRC on foreign lending, we reveal a negative and significant impact. More specifically, we find that with an increase of 1 percent of GPRC, foreign lending decreases by 3,108 percent. These results suggest that European banks decrease foreign loans, possibly because, owing to their nature, they are more exposed to geopolitical tensions, with potential consequences for international trade finance that could be significantly curtailed. In this regard, we believe that the increase in GPR does not have an impact on domestic lending, since the common economic and financial ecosystem to which both the bank and the borrower belong might not be subject to international tensions, and thus be immune to external dynamics. In addition, the shared environment in which the bank and borrower both operate may not necessarily lead to information asymmetry, or other types of distortions and biases that could potentially reduce bank lending. On the contrary, we believe

Table 6. Additional analysis: Tests for a country's geographical proximity to Russia/Ukraine and for dependence on Russian gas.

	Total loans (LN_LOAN_GR)	
Variables	(I)	(II)
LN_GPRC (−1)	−0.916	−0.136
	(0.637)	(0.409)
D_RU_UA_conflict	−15.793**	−12.096***
	(7.334)	(3.871)
LN_GPRC (−1)∗D_RU_UAconflict	−5.729**	−7.251***
	(2.285)	(1.420)
D_RU_UA_proximity	−13.306	
	(16.419)	
LN_GPRC (−1)∗D_RU_UAconflict∗D_RU_UAproximity	−2.498***	
	(0.866)	
D_Rugas		20.787
		(39.626)
LN_GPRC (−1)∗D_RU_UAconflict∗D_Rugas		−0.953*
		(0.542)
Control variables (−1)	Yes	Yes
Bank FE	Yes	Yes
Quarter FE	No	No
Cluster SE bank	Yes	Yes
N. of obs.	7.818	9.494
R-squared	0.105	0.076

This table presents the results of the estimation of panel regressions for our sample banks excluding Russia and Ukraine (i.e. the two countries at the center of the conflict), and taking into account (I) the geographical proximity to Russia/Ukraine, and (II) the dependence on Russian gas. Thus, our target variables are, in model (I), a triple interaction between LN_GRPC; the dummy Russia–Ukraine conflict (D_RU_UA_conflict), which equals 1 for the 2022Q1–2023Q4 period, and 0 otherwise; and the dummy Russia/Ukraine proximity (D_RU_UA_proximity), which equals 1 for those European countries closer to Russia and Ukraine, and for which Caldara and Iacoviello (2022) provided GPR data at the country level (i.e. Finland, Hungary, and Poland), and 0 otherwise. Instead, in model (II) we use a triple interaction between LN_GPRC; the D_RU_UA_conflict; and the D_RUgas, which equals 1 for those European countries more dependent on Russian gas in the years immediately before the conflict, and for which Caldara and Iacoviello (2022) provided GPR data at the country level (i.e. Finland, Germany, Hungary, Italy, Netherlands and Poland), and 0 otherwise. The period observed spans from 2008Q1 to 2023Q4. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank fixed-effects (FE) are included in the models. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

that foreign lending is affected by an increase in GPR. This might be due to the nature of bank loans, as well as the origin of operational and informational asymmetries, which may lead to a reduction in bank lending.

5.2. The role of bank ownership structure

Given that an established strand of the earlier literature has already documented that the response of bank lending to crisis conditions is contingent on bank ownership structure, we also analyze whether ownership structure can play a role in determining the lending response of banks to fluctuations in GPR. More specifically, in Table 5, through an interaction term between our target variable LN_GPRC and a dummy public (D_public) that equals 1 for bank public ownership and 0 otherwise, we investigate whether state ownership of banks is correlated with lending behavior over the business cycle to verify whether their lending is less responsive to geopolitical shocks than the lending of private banks. The findings are obtained, including only bank FE in column (I), and bank and quarter FE in column (II), over the 2008Q1–2023Q4 period. In line with De Haas and Van Horen (2013),

Table 7. Heckman two-step regression.

	Total loans	
Variables	D_H_GPR (I)	LN_LOANS_GR (II)
LN_GPRC (−1)		−1.715**
		(0.804)
SIZE (−1)	0.108***	−1.845
	(0.030)	(2.005)
ETA (−1)	0.041***	−0.086
	(0.011)	(0.711)
CIR (−1)	0.005***	−0.012
	(0.001)	(0.021)
NPL_GL (−1)	0.032***	−0.236
	(0.005)	(0.164)
LA_TA (−1)	0.014***	0.269*
	(0.003)	(0.155)
DEP_TA (−1)	0.003	−0.071
	(0.003)	(0.198)
ROAA (−1)	0.027	0.195
	(0.020)	(0.490)
GDPC (−1)	−0.076***	0.531**
	(0.017)	(0.238)
INFC (−1)	0.286***	0.101
	(0.015)	(0.171)
IMR		−0.000
		(0.010)
Bank FE	No	Yes
Quarter FE	Yes	Yes
Cluster SE bank	Yes	Yes
N. of. obs.	11.966	9.494
R-squared		0.096

This table reports the estimates of the Heckman two-step regression for our European sample banks over the 2008Q1–2023Q4 period. The first column (I) shows the first step (probit regression) of the Heckman two-step procedure, where the dependent variable is the dummy variable D_H_GPR, taking a value of 1 for banks headquartered in countries with GPR values above the average value of the sample, and 0 otherwise. The dependent variable in column (II) is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). In model (II) we include, as an additional control variable, the Inverse Mills Ratio (IMR) coefficient generated in the first step. The target variable is the natural logarithm of the country-specific GPRC index (LN_GPRC) developed by Caldara and Iacoviello (2022). See Section 3.2 for further details. As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Quarter fixed-effects (FE) are included in both models, while bank FE are included only in model (II). Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Albertazzi and Bottero (2014), and Dekle and Lee (2015), we find that the negative sign of the relationship between LN_GPRC and bank lending becomes positive when our target variable is interacted with the dummy public. Thus, our paper provides evidence that state-owned banks may play a credit smoothing role, displaying a more resilient lending behavior to geopolitical shocks than private banks. A potential explanation for this could be linked with the fact that their principal (the state) internalizes the benefits of a more stable macroeconomic environment (Micco and Panizza 2006). Therefore, credit stabilization is part of the objective function of state-owned banks.

Table 8. Baseline model controlling for country fixed-effects (FE) and country-time FE.

	Total loans (LN_TOT_LOANS_GR)	
Variables	(I)	(II)
LN_GPRC (−1)	−1.805***	−1.798***
	(0.682)	(0.640)
Control variables (−1)	Yes	Yes
Bank FE	No	No
Country FE	Yes	No
Quarter FE	Yes	No
Country*Quarter FE	No	Yes
Cluster SE bank	Yes	Yes
N. of. obs.	9.494	9.494
R-squared	0.047	0.279

This table reports the results of our baseline model run on our sample banks controlling for country fixed-effects (FE) (instead of bank FE). More specifically, in model (I), we control for country FE and quarter FE, while in model (II), we control for the interaction between country and quarter FE (Country*Quarter FE). The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). The target variable is the natural logarithm of the country-specific GPRC index (LN_GPRC) developed by Caldara and Iacoviello (2022). See Section 3.2 for further details. As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. The period observed spans 2008Q1 to 2023Q4. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

5.3. Effects of the Russia–Ukraine conflict

The long period considered (2008Q1–2023Q4) also allows us to take into consideration Russia's recent invasion of Ukraine (i.e. the European geopolitical event with the highest recorded peak for the GPR index developed by Caldara and Iacoviello (2022)) to verify its impact on the relationship between GPR and bank lending, as well as the role that a country's proximity to Ukraine and Russia, or its dependence on Russian gas, could play. Table 6 shows the results of these further additional analyses performed on a smaller bank sample than that used in the main analysis, owing to the exclusion of Russia and Ukraine (i.e. the two countries originally involved in the conflict). The findings are obtained including Bank FE, over the 2008Q1–2023Q4 period.

More specifically, to investigate whether a country's geographic proximity to Russia or Ukraine can play a role in the GPRC–total bank lending relationship (LN_LOANS_GR), in model (I) of Table 6, we use a triple interaction between LN_GRPC; the dummy Russia–Ukraine conflict (D_RU_UA_conflict), which equals 1 for the 2022Q1–2023Q4 period, and 0 otherwise; and the dummy Russia–Ukraine proximity (D_RU_UA_proximity), which equals 1 for those European countries closer to Russia and Ukraine (and for which Caldara and Iacoviello (2022) provided GPR data at the country level), namely Finland, Hungary, and Poland, and 0 otherwise.[16]

Additionally, to assess whether dependence on Russian gas could amplify the negative effect of GPRC on total lending by Europeans banks, in model (II) of Table 6, we use a triple interaction between LN_GPRC, D_RU_UA_conflict, and D_RUgas, which equals 1 for those European countries more dependent on Russian gas in the years immediately before the conflict[17] (and for which Caldara and Iacoviello (2022) provided GPR data at the country level), namely Finland, Germany, Hungary, Italy, Netherlands, and Poland,[18] and 0 otherwise.

As expected, we find that the recent Russian invasion of Ukraine amplified the negative effect of GPR on total lending, especially for those banks operating in countries located closer to Ukraine and Russia, and those more dependent on Russian gas.

Table 9. Baseline model with alternative measures for target variable.

Panel A – Alternative target measure for GPR: the country-specific historical geopolitical risk (GPRHC) index developed by Caldara and Iacoviello (2022)

Variables	Total loans (LN_LOANS_GR)
LN_GPRHC (−1)	−1.657**
	(0.758)
Control variables (−1)	Yes
Bank FE	Yes
Quarter FE	Yes
Cluster SE bank	Yes
N. of obs.	9.442
R-squared	0.094

Panel B – Alternative target measure for GPR: the global geopolitical risk index determined using data collected by Google Trends (GPR_GT)

Variables	Total loans (LN_LOANS_GR)
LN_GPR_GT (−1)	−25.147**
	(11.757)
Control variables (−1)	Yes
Bank FE	Yes
Quarter FE	Yes
Cluster SE bank	Yes
N. of obs.	11.302
R-squared	0.106

This table reports the results of our baseline model run on our sample banks over the 2008Q1–2023Q4 period, using the following two alternative target measures for GPR: the country-specific historical geopolitical risk (GPRHC) index developed by Caldara and Iacoviello (2022), see Panel A, and the global geopolitical risk index collected by Google Trends (GPR_GT), see Panel B. Since both GPRHC and GPR_GT are highly skewed, we use their natural logarithms (LN_GPRHC and LN_GPR_GT), which are normally distributed. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank and quarter fixed-effects (FE) are included in the model. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

6. Robustness tests

To strengthen the validity of our main results, a set of robustness checks are run. First, to reduce the endogeneity concerns that result from sample selection bias, we employ the Heckman's (1978) two-step method. The issue of sample selection bias could potentially affect the analysis of the relationship between the GPR index and bank loans, since the issue may arise when the sample used in an analysis is not randomly selected. For our purposes, certain countries or regions in the sample may be included/excluded simply for their GPR data levels or availability, thus rendering our sample composition non-random. As a result, the observed relationship between the GPR index and bank loans may be distorted, leading to inaccurate conclusions or misleading interpretations. The rationale for the use of the Heckman method is twofold. First, there is a possibility that GPR affects not only the volume of lending, but also the bank's decision to lend at all in certain periods or to certain sectors. In such cases, the observed loan data may be subject to selection bias, since we only observe lending outcomes when a bank chooses to engage in lending activity, which may itself be endogenous to geopolitical conditions. Second, GPR may correlate with unobserved factors (such as changes in credit demand, borrower quality, or macroeconomic sentiment) that simultaneously affect both the probability of issuing loans and the volume of those loans, thereby biasing ordinary least squares estimates.

Table 10. Baseline model with the European Central Bank (ECB)'s unconventional liquidity injections.

Variables	Total loans (LN_LOANS_GR)
LN_GPRC (−1)	−1.235**
	(0.626)
Control variables (−1)	Yes
D_UNC_LIQ_INJ	Yes
Bank FE	Yes
Quarter FE	No
Cluster SE bank	Yes
N. of obs.	9.494
R-squared	0.060

This table reports the results of our baseline model run on our sample banks taking into account the unconventional liquidity injections realized by the European Central Bank (ECB) over the 2011Q4–2023Q4 period. Thus, the dummy variable D_UNC_LIQ_INJ equals 1 in the quarter in which the ECB provided liquidity to eurozone banking systems through the unconventional liquidity measures longer-term refinancing operations (LTROs) and targeted longer-term refinancing operations (TLTROs), and 0 otherwise. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). The target variable is the natural logarithm of the country-specific GPRC index (LN_GPRC) developed by Caldara and Iacoviello (2022). See Section 3.2 for further details. As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank fixed-effects (FE) are included in the model. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

The Heckman selection model corrects for this potential bias by modeling the lending decision in two stages: the first step estimates the probability of a positive lending observation (selection equation), and the second step estimates the determinants of lending volumes conditional on selection (outcome equation). This approach allows us to account for the non-random nature of lending decisions and the influence of GPR at both the extensive (whether to lend) and intensive (how much to lend) margins.

The results of this additional test, shown in Table 7, reveal that the relationship between GPR and total loans remains the same as that in the baseline analysis (negative sign), showing the lack of possible endogeneity biases coming from the sample selection.

Next, to reduce the concerns deriving from omitted variables correlated with unobserved country characteristics affecting bank lending, as a robustness check, we run our baseline model including country FE (in place of bank FE) in addition to quarter FE in column (I), and the interaction between country and quarter FE in column (II). The results of our target variable LN_GPRC remain qualitatively unchanged when controlling for country characteristics through FE, suggesting that total loans is directly affected by the macroeconomic conditions already included, rather than being driven by unobserved country-level factors (Table 8).

We further test the consistency of our results using an alternative GPR definition. First, we run our baseline model substituting the target variable LN_GPRC with the historical GPR index (GPRHC), developed by Caldara and Iacoviello (2022) at the country level. Unlike the GPRC index, the main difference is that GPRHC is computed using three newspapers, but starting in 1900 (compared with 10 newspapers since 1985). See Section 3.2 for details on the methodology. Since GPRHC is also highly skewed, we use its natural logarithm (LN_GPRHC), which is normally distributed.[19] The results, shown in Panel A of Table 9, confirm our baseline findings, that is, a negative relationship between GPR (also when using GPRHC) and total lending. More specifically, total lending decreases by 1,657 percent as a consequence of an increase in GPRHC of 1 percent.

Table 11. Baseline model controlling for fintech competition.

Variables	Total loans (LN_LOANS_GR)
LN_GPRC (−1)	−1.797**
	(0.778)
Mobile_pay (−1)	−6.584
	(5.013)
Control variables (−1)	Yes
Bank FE	Yes
Quarter FE	Yes
Cluster SE bank	Yes
N. of obs.	9.494
R-squared	0.060

This table reports the results of our baseline model run on our sample banks including a proxy for fintech among the control variables. Following Demir et al. (2022), the total payments made by mobile phones to pay bills (Mobile_pay) is a reliable measure of fintech market size and usage. The variable Mobile bill payments was drawn from the World Bank's Global Financial Inclusion Database (Findex). The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). The target variable is the natural logarithm of the country-specific GPRC index (LN_GPRC) developed by Caldara and Iacoviello (2022). See Section 3.2 for further details. As controls, we also include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. The period observed spans 2008Q1 to 2023Q4. Bank fixed-effects (FE) and quarter FE are included in the model. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

We then test the consistency of our results using another alternative GPR measure collected by a different provider. More precisely, we collect data from Google Trends, a publicly available database introduced in 2008 to provide statistics for relative internet search volumes of queries identified by specific keywords. One of the advantages of internet searches is the access to 'real time' data, particularly being able to capture sentiment indicators (Simionescu and Zimmermann 2017). By selecting the keyword 'geopolitical risk,' we collect data on GPR Google Trends (GPR_GT) as a proxy for stakeholder sentiment relating to geopolitical events. Since GPR_GT is also highly skewed, we use its natural logarithm (LN_GPR_GT), which is normally distributed. Data are collected with monthly frequency, and then adjusted to quarterly frequency in line with all other variables used in the study. This is a global index, thus it is not available at the country level, as in the case of those developed by Caldara and Iacoviello (GPRC and GPRHC). However, LN_GPR_GT shows a high level of correlation with LN_GPRC, equal to 0.688 over the 2008Q1–2023Q4 period.

In addition, as shown in Panel B of Table 9, the alternative measure based on information derived from Google Trends confirms the validity of our main results, since the coefficient of LN_GPR_GT is negative and significant, thus implying a decrease in bank lending for an increase in GPR.

The period considered requires the need to control for the effects of those unconventional liquidity injections through which the European Central Bank (ECB) introduced unprecedent liquidity into eurozone banks to restore lending after the sovereign debt and the pandemic crises. Thus, the baseline model is run using the dummy ECB's unconventional liquidity injections (D_UNC_LIQ_INJ) in place of quarter FE. The variable D_UNC_LIQ_INJ is equal to 1 in the quarter in which the ECB, to stimulate bank lending after the credit crunch resulting from the sovereign debt crisis, provided liquidity to eurozone banking systems through the unconventional liquidity measures longer-term refinancing operations and targeted longer-term refinancing operations,[20] and 0 otherwise. The results, shown in Table 10, confirm the negative and significant relationship between GPRC and total lending.

Table 12. Baseline model without Russia and Ukraine.

Variables	Total loans (LN_LOANS_GR)
LN_GPRC (−1)	−1.807**
	(0.755)
Control variables (−1)	Yes
Bank FE	Yes
Quarter FE	Yes
Cluster SE bank	Yes
N. of obs.	7.818
R-squared	0.096

This table reports the results of our baseline model run on our sample banks excluding those belonging to Russia and Ukraine (i.e. the two countries at the center of the conflict) over the 2008Q1–2023Q4 period. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). The target variable is the natural logarithm of the country-specific GPRC index (LN_GPRC) developed by Caldara and Iacoviello (2022). See Section 3.2 for further details. As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank and quarter fixed-effects (FE) are included in the model. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Next, given that this study covers a long period, the findings related to credit growth may be confounded with the emergence of non-banks and other financial intermediaries (such as fintech institutions) in facilitating the flow of funds from the financial side to the real side of the economies. These developments may indeed influence aggregate credit dynamics and potentially confound the relationship between GPR and bank-based credit growth. To address these confounding factors, we use a control variable representing the penetration rate of such alternative financial intermediaries at the country level. Following Demir et al. (2022), the total payments made by mobile phones to pay bills (Mobile_pay) is a reliable measure of fintech market size and usage. The variable Mobile bill payments was drawn from the World Bank's Global Financial Inclusion Database (Findex). Table 11 confirms our baseline results: a negative GPR–bank lending policy relationship also exists when we control for alternative finance (i.e. fintech) penetration.

Next, to ensure that our results are not driven by banks in countries more affected by the most acute geopolitical event in Europe for the period considered (2008Q1–2023Q4), we run our baseline model of Equation (1), including directly both bank and quarter FE, on a subsample excluding Russia and Ukraine (Table 12). Examining the results for the other European countries, we find that these results are qualitatively consistent. More specifically, we find that for an increase in GPRC of 1 percent, total lending decreases by 1,807 percent, with potential implications for both households and corporate access to credit.

Subsequently, since our analysis relies on a heterogenous cross-country sample of European banks, we further test its robustness by performing several additional analyses in our baseline econometric setting on specific subsamples to assess whether the GPR–bank lending linkage varies significantly owing to bank characteristics or different operating environments.

Panel A of Table 13 shows a positive result for large and listed banks versus a negative relationship for non-listed banks. These results mean that only the credit behaviors of large and listed banks are unaffected by geopolitical events. One possible explanation for this is that the large and listed banks are generally more diversified than the non-listed banks, and consequently, their credit levels would be less affected under conditions of uncertainty. Moreover, Panel B of Table 13 reveals that the characteristics of the operating environment in which the banks operate also play a role in the relationship between GPR and bank lending. More specifically, we find that geopolitical threats have a negative impact on credit growth only for those banks located in

Table 13. Baseline model by different subsamples.

Panel A – Bank characteristics

	Total loans (LN_LOANS_GR)			
Variables	SIZE_q1	SIZE_q4	Non-listed	Listed
LN_GPRC (−1)	−6.210	0.501**	−3.946***	1.103*
	(7.271)	(0.222)	(1.021)	(0.604)
Control variables (−1)	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Cluster SE bank	Yes	Yes	Yes	Yes
N. of obs.	1.152	3.985	5.868	3.626
R-squared	0.339	0.069	0.146	0.129

Panel B – Operating environment

	Total loans (LN_LOANS_GR)					
Variables	GDPC_q1	GDPC_q4	Non-eurozone countries	Eurozone countries	EPU_q1	EPU_q4
LN_GPRC (−1)	−3.372***	2.115	−5.762***	1.293**	0.811	−7.601***
	(0.870)	(3.080)	(1.324)	(0.537)	(1.221)	(1.938)
Control variables (−1)	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE bank	Yes	Yes	Yes	Yes	Yes	Yes
N. of obs.	2.204	3.223	4.897	4.597	1.116	3.484
R-squared	0.551	0.238	0.179	0.100	0.839	0.231

This table reports the estimates of our baseline model tested employing different subsamples that control for bank characteristics, such as size (bottom vs top quartile by size, SIZE_q1, and SIZE_q4, respectively) and listed vs non-listed banks (see Panel A), as well as for operating environment, such as the income level of the country (bottom vs top quartile by GDPC, GDPC_q1, and GDPC_q4, respectively), inclusion or not in the eurozone, and the measurement of the country's economic policy uncertainty (EPU) index (developed by Baker, Bloom, and Davis 2016; bottom vs top quartile by EPU, EPU_q1, and EPU_q4, respectively; see Panel B). The period considered spans 2008Q1 to 2023Q4. The dependent variable is the natural logarithm of the quarterly average growth rate of total customer loans (LN_LOANS_GR). The target variable is the natural logarithm of the country-specific GPRC index (LN_GPRC) developed by Caldara and Iacoviello (2022). See Section 3.2 for further details. As controls, we include variables based on accounting data (SIZE, ETA, CIR, NPL_GL, LA_TA, DEP_TA, and ROAA) and on macroeconomic data (GDPC and INFC). See Table 1 for a description of the variables. All the explanatory variables are lagged by one-quarter. All covariates based on accounting data not measured as natural logarithms are winsorized at 1 per cent of each tail. Bank and quarter fixed-effects (FE) are included in the model. Clustered standard errors by bank are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at the 1%, 5%, and 10% levels, respectively, in two-tailed tests.

non-eurozone countries and those with lower GDP income levels. Therefore, eurozone countries with higher levels of economic development should be able to continue their lending activities and not be affected by GPR. Additionally, Panel B of Table 13 shows that the negative relationship between GPR and bank lending exists only for those countries with a high EPU index, which reflects the unpredictability surrounding fiscal, monetary, and regulatory policies.[21] This result corresponds with the prior literature that found that both the amount and cost of bank loans can be also driven by country-level heterogeneities in EPU (Ashraf and Shen 2019; Bordo, Duca, and Koch 2016; and Hu and Gong 2019).

7. Conclusions

Motivated by the increase in international geopolitical tensions that have threatened the global economy, such as the recent Russian invasion of Ukraine, we study the relationship between GPR and bank lending in Europe through the novel country-specific GPR index developed by Caldara and Iacoviello (2022). More specifically, using data from a sample of European banks from 18 countries over the 2008Q1–2023Q4 period, observed at quarterly frequency, we find that GPR reduces total bank credit growth. Through additional analyses, we then perform a deeper investigation by geographical location of European bank lending, distinguishing between domestic and foreign. Our findings show that geopolitical tensions do not exert a significant influence on domestic lending, dampening only foreign loans, with negative potential consequences for the international trade conducted by those European banks that could be curtailed.

We also find a more resilient lending behavior in response to geopolitical shocks from state-owned banks compared with private banks, which shows that the response of bank total lending to GPR is contingent on the bank ownership structure.

Moreover, the prolonged timeframe enabled us to incorporate and assess Russia's recent invasion of Ukraine to verify its impact on the relationship between GPR and bank lending. As expected, the recent Russia–Ukraine tensions amplified the negative effect of GPR on total lending, especially for those banks operating in countries located closer to Ukraine and Russia, or those more dependent on Russian gas.

Further analyses of bank characteristics reveal that the credit behaviors of large and listed banks are unaffected by GPR. One possible explanation for this is that larger and listed banks are generally more diversified, and therefore their credit levels would be less affected in an environment of geopolitical uncertainty. Finally, we find that those countries with higher values of GDP that belong to the eurozone and have low EPU are less vulnerable to geopolitical tensions, and thus can continue their lending activities.

Overall, our results support the importance for banks, regulators, and policymakers to take into consideration the impact of GPR on the banking sector, and in particular, on bank lending.

For banks, we identify substantial heterogeneity in their responses to GPR, driven by factors related to their ownership structure, bank characteristics (such as size), or different operating environments (such as level of GDP). This study also highlight changes in the credit allocation of banks in response to geopolitical uncertainty. More specifically, we show that banks reduce total lending through foreign lending, illustrating how they adapt their credit strategies to manage risk under geopolitical uncertainty. Thus, for banks, it is fundamental that, in future, they introduce ad hoc risk management strategies in response to GPR to address its effects on their financial statements, which can indirectly negatively affect real economic activity. This implies that bank exposure to GPR will need to be identified and included among potentially relevant risk drivers.

Moreover, for regulators, the adoption of adequate monitoring activities is important for promptly minimizing the potential adverse consequences of increasing GPR.

Finally, our results are policy relevant. For policymakers in the source countries of lending banks, understanding the effects of geopolitical tensions can help gauge the cross-border bank lending activities of their banks, and thus, domestic credit conditions. For policymakers in the borrowing countries, comprehending the impact of geopolitical tensions can help with assessing the credit supply via cross-border bank lending to their country to better manage periods of volatile bank flows.

Notes

1. Consistently, Caldara and Iacoviello (2022) showed that geopolitical uncertainty is weakly correlated with stock market volatility indicators (such as VIX) and economic policy uncertainty (EPU) indexes (such as the news-based EPU index of Baker, Bloom, and Davis 2016), and that it is not Granger-caused by macroeconomic and financial development. See also Fiorillo et al. (2024).
2. GPR differs from other macroeconomic uncertainty indicators in the following significant ways (Phan, Tran, and Iyke 2022). First, it captures infrequent but cataclysmic events that may remain hidden for decades (Guttentag and Herring 1997). Second, it covers all domestic and international affairs, distinct from other political instability indicators, which merely focus on domestic political issues (Alsagr and Almazor 2020). Third, when compared with other macroeconomic events, geopolitical events (e.g. terrorist acts) are more difficult to predict (Dissanayake, Mehrotra, and Wu 2020).
3. For a detailed description of all adverse implications of GPR for banks, see Catalan et al. 2023 (p. 85) and Dieckelmann et al. 2024 (p. 98).
4. To address the dynamics involved in the European context, we focus our attention specifically on the banks headquartered in the sample countries.
5. Data on the GPR indexes at a country level are available for 44 advanced and emerging countries, but only 18 of them are European countries. See https://www.matteoiacoviello.com/gpr_country.htm.
6. The 10 newspapers considered by Caldara and Iacoviello for measuring GPR are the *Chicago Tribune*, *The Daily Telegraph*, the *Financial Times*, *The Globe and Mail*, *The Guardian*, the *Los Angeles Times, The New York Times*, *USA Today*, *The Wall Street Journal*, and *The Washington Post*.
7. The three newspapers considered by Caldara and Iacoviello for measuring the GRPH are *The New York Times*, the *Chicago Tribune*, and *The Washington Post*.

8. For GPR computed at the global level, Caldara and Iacoviello also constructed two sub-indexes: the geopolitical threat (GPRT) index, which includes words belonging to Categories 1–5 above, and the geopolitical act (GPRA) index, which includes words belonging to Categories 6 to 8.
9. The 18 European countries for which GPR is available at the country level (GPRC and GPRHC) are Belgium (BE), Switzerland (CH), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), the United Kingdom (UK), Hungary (HU), Italy (IT), the Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Russia (RU), Sweden (SE), Turkey (TR), and Ukraine (UA).
10. As a robustness test, we run the baseline model also adjusting both the daily frequency of our target variable LN_GPRC and the quarterly frequency of all other covariates, to annual frequency (instead of quarterly frequency, as shown in all our analyses). However, the results for our target variable LN_GPRC lose their significance (they are not reported, but are available on request). Indeed, observing daily variables, such as the GRP index, with quarterly frequency (which is the closest frequency to the daily one) is better than yearly frequency because it provides a more complete picture by capturing short-term fluctuations and seasonal patterns that are smoothed out or completely missed when using annual data. This higher frequency data reveals more dynamic changes, leads to more precise modeling, and avoids data aggregation bias, ultimately resulting in more accurate forecasts and a better understanding of the underlying economic processes.
11. We performed the Wooldridge test and the results show that the model does not suffer from any autocorrelation problems.
12. As robustness tests, we run the model described in Equation (1) using, first, country FE (in place of bank FE) in addition to quarter FE, and second, the interaction between country and quarter FE. As shown in Table 8, in both cases, we obtained very similar results on our target variable LN_GPRC.
13. As a robustness test, we use the growth rate of deposits from customers (in place of DEP_TA) and obtain very similar results (not reported, but available on request).
14. As a robustness test, we use the return on average equity (ROAE), in place of ROAA, and obtain very similar results (not reported, but available on request).
15. On the basis of the results of the variance inflation factor (VIF) test, it emerges that no multicollinearity problems exist.
16. As a robustness test, we also run the analysis including first Norway in the dummy proximity equalling 1, and then Turkey, obtaining similar results (not reported, but available on request).
17. Data on EU reliance on Russian gas are available from Eurostat.
18. All these countries showed a share in total imports in 2020 of Russian natural gas in percentages above 30 percent. Source: Eurostat.
19. The two alternative target variables developed by Caldara and Iacoviello (2022) at the country level (LN_GPRC and LN_GPRHC) used in the main analysis and the robustness tests, respectively, show, on average, a high level of correlation equal to 0.96 over the 2008Q1–2023Q4 period.
20. The longer-term refinancing operations (LTROs) programme includes two auctions – the first occurred in December 2011 and the second in February 2012 – both characterized by a maturity of 3 years. Meanwhile, the targeted longer-term refinancing operations (TLTROs) programme includes three tranches: the TLTROs I in 2014Q3, the TLTROs II in 2016Q2, and TLTROs III in 2019Q3. Each of them is composed by several auctions (8 for TLTROs I, 4 for TLTROs II, and 10 for TLTROs III), and is characterized by a maturity of 4 years. See the ECB website for more details.
21. The country-specific EPU index was developed by Baker, Bloom, and Davis (2016) and uses a text-mining approach to capture the policy uncertainty apparent in newspaper articles and other sources, and considers both short-term and long-term uncertainty concerns. We collected data on the EPU index for those countries considered in our analysis at monthly frequency, and then adjusted by quarter.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

We declare that data used for this paper are available upon request.

Notes on contributors

Laura Chiaramonte is Full Professor of Banking and Finance at University of Verona (Italy). Her main research interests are in empirical banking, financial regulation and structured finance. She has published in international peer-reviewed journals.

Federico Mecchia is PhD student at the Interuniversity PhD in Accounting and Management at University of Udine jointly with University of Verona (Italy). His main research interests are in empirical banking and finance with a specific focus on geopolitical risk.

Andrea Paltrinieri is Associate Professor of Banking and Finance at the Catholic University of Sacred Heart (Milan, Italy). His main fields of research deal with Islamic finance, especially sukuk and Islamic banks, Sovereign Wealth Funds, in terms of asset allocation and impact on global financial crises, commodities and finance' bibliometric reviews. He has published in international peer-reviewed journals.

Stefano Piserà is Assistant Professor in Corporate Finance and Financial Markets at University of Genoa (Italy). His main research interests are in applied finance and banking, economics of financial markets, sustainable finance, empirical corporate finance He has published in international peer-reviewed journals.

ORCID

Andrea Paltrinieri http://orcid.org/0000-0002-8172-9199

References

Albertazzi, U., and M. Bottero. 2014. "Foreign Bank Lending: Evidence from the Global Financial Crisis." *Journal of International Economics* 92:S22–S35. https://doi.org/10.1016/j.jinteco.2014.01.002.

Alsagr, N., and S. F. V. H. Almazor. 2020. "Oil Rent, Geopolitical Risk and Banking Sector Performance." *International Journal of Energy Economics and Policy* 10 (5): 305–314. https://doi.org/10.32479/ijeep.9668.

Ashraf, B. N., and Y. Shen. 2019. "Economic Policy Uncertainty and Banks' Loan Pricing." *Journal of Financial Stability* 44:100695. https://doi.org/10.1016/j.jfs.2019.100695.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics* 131 (4): 1593–1636. https://doi.org/10.1093/qje/qjw024.

Banerjee, A. K., A. Sensoy, and J. W. Goodell. 2024. "Volatility Connectedness between Geopolitical Risk and Financial Markets. Insights from Pandemic and Military Crisis Periods." *International Review of Economics and Finance* 96:103740. https://doi.org/10.1016/j.iref.2024.103740.

Behn, M., J. H. Lang, and A. Reghezza. 2025. "120 Years of Insight Geopolitical Risk and Bank Solvency." *Economics Letters* 247:112168. https://doi.org/10.1016/j.econlet.2025.112168.

Bordo, M. D., J. V. Duca, and C. Koch. 2016. "Economic Policy Uncertainty and the Credit Channel: Aggregate and Bank Level US Evidence over Several Decades." *Journal of Financial Stability* 26:90–106. https://doi.org/10.1016/j.jfs.2016.07.002.

Caldara, D., and M. Iacoviello. 2022. "Measuring Geopolitical Risk." *American Economic Review* 112 (4): 1194–1225. https://doi.org/10.1257/aer.20191823.

Carletti, E., I. Goldstein, and A. Leonello. 2020. The Interdependence of Bank Capital and Liquidity, BAFFI CAREFIN Centre Research Paper, N. 128.

Carlson, M., H. Shan, and M. Warusawitharana. 2013. "Capital Ratios and Bank Lending: A Matched Bank Approach." *Journal of Financial Intermediation* 22 (4): 663–687. https://doi.org/10.1016/j.jfi.2013.06.003.

Catalan, M., M. S. Dovi, S. Fendoglu, O. Khadarina, J. Mok, T. Okuda, H. R. Tabarraei, T. Tsuruga, and M. Yenice. 2023. Geopolitics and Financial Fragmentation: Implications for Macro-financial Stability, in Global Financial Stability Report, International Monetary Fund, April.

Chi, Q., and W. Li. 2017. "Economic Policy Uncertainty, Credit Risks and Banks' Lending Decisions: Evidence from Chinese Commercial Banks." *China Journal of Accounting Research* 10 (1): 33–50. https://doi.org/10.1016/j.cjar.2016.12.001.

Choi, S., and J. Havel. 2025. "Geopolitical Risk and U.S. Foreign Portfolio Investment: A Tale of Advanced and Emerging Markets." *Journal of International Money and Finance* 151:103253. https://doi.org/10.1016/j.jimonfin.2024.103253.

Danisman, G. O., O. Ersan, and E. Demir. 2020. "Economic Policy Uncertainty and Bank Credit Growth: Evidence from European Banks." *Journal of Multinational Financial Management* 57–58:100653. https://doi.org/10.1016/j.mulfin.2020.100653.

De Haas, R., and N. Van Horen. 2013. "Running for the Exit? International Bank Lending during a Financial Crisis." *The Review of Financial Studies* 26 (1): 244–285. https://doi.org/10.1093/rfs/hhs113.

Dekle, R., and M. Lee. 2015. "Do Foreign Bank Affiliates cut Their Lending More than the Domestic Banks in a Financial Crisis?" *Journal of International Money and Finance* 50:16–32. https://doi.org/10.1016/j.jimonfin.2014.08.005.

Del Giovane, P., G. Eramo, and A. Nobili. 2011. "Disentangling Demand and Supply in Credit Developments: A Survey-based Analysis for Italy." *Journal of Banking and Finance* 35 (10): 2719–2732. https://doi.org/10.1016/j.jbankfin.2011.03.001.

Demir, A., V. Pesqué-Cela, Y. Altunbas, and V. Murinde. 2022. "Fintech, Financial Inclusion and Income Inequality: A Quantile Regression Approach." *The European Journal of Finance* 28 (1): 86–107. https://doi.org/10.1080/1351847X.2020.1772335.

Demir, E., and G. O. Danisman. 2021. "The Impact of Economic Uncertainty and Geopolitical Risks on Bank Credit." *The North American Journal of Economics and Finance* 57:101444. https://doi.org/10.1016/j.najef.2021.101444.

Dieckelmann, D., C. Kaufmann, P. M. Larkou, C. Negri, C. Pancaro, and D. Robler. 2024. Turbolent Times: Geopolitical Risk and its Impact on Euro Area Financial Stability, Special Features in Financial Stability Review, European Central Bank, May.

Dissanayake, R., V. Mehrotra, and Y. Wu. 2020. Geopolitical Risk and Corporate Investment, Working paper. SSRN Electronic Journal, available on https://www.ssrn.com/abstract = 3222198.

Enria, A. 2022. Better Safe than Sorry: Banking Supervision in the Wake of Exogeneous Shocks, Speech Given at the Austrian Financial Market Authority Supervisory Conference, October.

Feng, C., L. Han, S. Vigne, and Y. Xu. 2023. "Geopolitical Risk and the Dynamics of International Capital Flows." *Journal of International Financial Markets, Institutions & Money* 82:101693. https://doi.org/10.1016/j.intfin.2022.101693.

Fiorillo, P., A. Meles, L. R. Pellegrino, and V. Verdoliva. 2023. "Geopolitical Risk and Stock Liquidity." *Finance Research Letters* 54:1–8. https://doi.org/10.1016/j.frl.2023.103687.

Fiorillo, P., A. Meles, L. R. Pellegrino, and V. Verdoliva. 2024. "Geopolitical Risk and Stock Price Crash Risk: The Mitigating Role of ESG Performance." *International Review of Financial Analysis* 91:102958. https://doi.org/10.1016/j.irfa.2023.102958.

Guttentag, J. M., and R. J. Herring. 1997. "Disaster Myopia in International Banking." *The Journal of Reprints for Antitrust Law and Economics* 27:37–74.

Heckman, J. J. 1978. "Dummy Endogenous Variables in a Simultaneous Equation System." *Econometrics* 46 (4): 931–959. https://doi.org/10.2307/1909757.

Hu, S., and D. Gong. 2019. "Economic Policy Uncertainty, Prudential Regulation and Bank lending." *Finance Research Letters* 29 (C): 373–378. https://doi.org/10.1016/j.frl.2018.09.004.

Kapan, T., and C. Minoiu. 2013. "Balance Sheet Strength and Bank Lending During the Global Financial Crisis." *International Monetary Fund Working Paper* 102, May.

Mertzanis, C., and I. Tebourbi. 2025. "Geopolitical Risk and Global Green Bond Market Growth." *European Financial Management* 31: 26–71. https://doi.org/10.1111/eufm.12484.

Micco, A., and U. Panizza. 2006. "Bank Ownership and Lending Behavior." *Economics Letters* 93 (2): 248–254. https://doi.org/10.1016/j.econlet.2006.05.009.

Nguyen, T. C., and T. H. Thuy. 2023. "Geopolitical Risk and the Cost of Bank Loans." *Finance Research Letters* 54:103812. https://doi.org/10.1016/j.frl.2023.103812.

Nguyen, T. C., and T. H. Thuy. 2024. "Bank Wholesale Funding in an era of Rising Geopolitical Risk." *The World Economy* 47 (11): 4306–4330. https://doi.org/10.1111/twec.13620.

Phan, D. H. B., V. T. Tran, and B. N. Iyke. 2022. "Geopolitical Risk and Bank Stability." *Finance Research Letters* 46 (Part B): 102453. https://doi.org/10.1016/j.frl.2021.102453.

Piserà, S., L. Chiaramonte, A. Paltrinieri, and F. Pichler. 2024. "Firm Systematic Risk after the Russia–Ukraine Invasion." *Finance Research Letters* 64:105489. https://doi.org/10.1016/j.frl.2024.105489.

Salisu, A. A., L. Lasisi, and J. P. Tchankam. 2022. "Historical Geopolitical Risk and the Behaviour of Stock Returns in Advanced Economies." *The European Journal of Finance* 28 (9): 889–906. https://doi.org/10.1080/1351847X.2021.1968467.

Shabir, M., P. Jiang, Y. Shahab, and P. Wang. 2023. "Geopolitical, Economic Uncertainty and Bank Risk: Do CEO Power and Board Strength Matter?" *International Review of Financial Analysis* 87:102603. https://doi.org/10.1016/j.irfa.2023.102603.

Simionescu, M., and K. F. Zimmermann. 2017. Big Data and Unemployment Analysis, Global Labor Organization (GLO) Discussion Paper, No 81.

Trinh, H. H., and T. P. Tran. 2024. "Global Banking Systems, Financial Stability, and Uncertainty: How Have Countries Coped with Geopolitical Risks?" *International Review of Economics & Finance* 96:103647. https://doi.org/10.1016/j.iref.2024.103647.

Vives, X. 2014. "Strategic Complementarity, Fragility and Regulation." *Review of Financial Studies* 27 (12): 3547–3592. https://doi.org/10.1093/rfs/hhu064.

Wang, X., Y. Wu, and W. Xu. 2024. "Geopolitical Risk and Investment." *Journal of Money, Credit and Banking* 56 (8): 2023–2059. https://doi.org/10.1111/jmcb.13110.

Wang, Y., G. Song, and Y. Lu. 2025. "Geopolitical Risk, Bank Regulation, and Systemic Risk. A Cross-Country Analysis." *Finance Research Letters* 76:106893. https://doi.org/10.1016/j.frl.2025.106893.

Zhou, L., G. Gozgor, M. Huang, and M. C. K. Lau. 2020. "The Impact of Geopolitical Risks on Financial Development: Evidence from Emerging Markets." *Journal of Competitiveness* 12 (1): 93–107. https://doi.org/10.7441/joc.2020.01.06.