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Geopolitical risk and cross-border bank lending

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Abstract

How does geopolitical risk affect cross-border bank lending? To examine this question, we exploit a rich cross-border bank lending data set from the UK which records banks' large exposures to individual firms and match this with a firm-level measure of geopolitical risk, derived from firms' earnings call reports. Combining granular firm-level data points with tight fixed effect specifications, we find that a one standard deviation increase in geopolitical risk causes cross-border bank lending to decline by around 4% after one year. This effect is not uniform: lending to financial sector firms declines most, while energy and defence sectors show no significant impact; also better-capitalised banks are less sensitive to borrower risk. Effects vary with geopolitical alignment between bank and firm nationalities and are more significant for sanctions-related risk. Finally, local projections show that geopolitical risk transmits to cross-border lending via macroeconomic aggregates and asset prices, with transmission influenced by credit growth dynamics and sanctions as the primary risk driver.

Key words: Banking, geopolitics, cross-country spillovers, interconnections.

JEL classification: F3, F34, F51, G21.

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1 Introduction

Geopolitical risk has reemerged in recent years as a key factor shaping the global economic and financial landscape. Recent global events such as the Russia's invasion of Ukraine, Brexit, U.S.-China tensions, and renewed tensions in the Middle East have brought geopolitical risk to the forefront. Both the IMF and the ECB have devoted recent chapters in their flagship financial stability publications to voice concerns about the impact of geopolitical risk on financial stability. Within the financial sector, geopolitical risks are increasingly recognized as systemic threats and consistently rank among the top concerns for investors, for example, as shown in the Bank of England (2025) Systemic Risk Survey Results.

But despite this there has been little academic work examining how banks respond to increased geopolitical risk in the countries to which they lend. Many banks operate at the global level and are a major source of capital flows to countries which experience heightened geopolitical risk; and in turn geopolitical risk has negative implications for bank capital and profitability (Behn et al. (2025)).

The UK is an ideal environment to study the international propagation of geopolitical shocks. It is host to over 250 banks from around the world, including countries which are or have been at the centre of recent geopolitical tensions. The UK is a major financial centre where foreign banks channel funds to lend via London to engage in cross-border lending (see for example Bussière et al. (2020)) and so we are able to capture a large proportion of these banks' cross-border lending and exposure to the country of interest. At the same time the UK is a major source of finance for the firms borrowing from the banks in the dataset and the firms are unlikely to be able to fully substitute and borrow from elsewhere - meaning that any change in bank lending is likely to be of economic importance to the borrower.

We examine the impact on cross-border lending of geopolitical risk using two unique datasets. First, we use the large exposures dataset, based on supervisory reporting, which captures data on UK banks' individual loans to their largest and most important clients globally. As a result, we focus on lending where the relationship with the firm is likely to be of importance to the bank's balance sheet and the bank is likely to be taking decisions based on in-depth monitoring of the firm. Second, we measure individual firms exposure to geopolitical risk based on earnings calls from the NL analytics platform. We are thus able to match individual firms and their exposure to geopolitical risk to the bank they are borrowing from in the UK. Combing these datasets at the individual firm level allows us to examine how banks respond to geopolitical risk faced by their key clients and explore a number of different channels and heterogeneities.

The high level of granularity means that we can explore the effect of geopolitical risk at the individual firm level. We do this in cross-country panel regressions where the granularity of the data allows us to deploy tight fixed effect specifications. These specifications allow us to estimate a causal effect of firm-level geopolitical risk on banks' large exposures to firms with a reasonable degree of certainty.

We make a number of contributions in the paper. First, we are able to contribute to the emerging literature on geopolitical risk and bank lending (see Niepmann and Shen (2024) and Phan et al. (2022) but explore the effect of geopolitical risk measured at the firm-level. We expect lending by banks to decline in the face of geopolitical risks in borrowers, consistent with the hypothesis that in general banks take into accounts risks in their borrowers when making lending decisions. This is likely to be especially true in our dataset given that it comprises of large exposures, which are to larger firms to which banks have extended significant lending and so banks will be monitoring risks closely at the individual firm level. Our main baseline result is that firm-level geopolitical risk does indeed have significant and causal effect on cross-border bank lending: a one standard deviation increase in geopolitical risk decreases cross-border bank lending by around 4% after one year.

We then explore a number of heterogeneities. We also contribute by exploring how banks' response to geopolitical risk depends on the sector of the firm facing geopolitical risk and find that banks cut lending to firms in the financial sector while the point estimate is negative albeit insignificant for lending to firms in other tradable sectors such as manufacturing. In contrast, banks don't significantly change their lending to firms in defence and energy-related sectors following increases in firm-level geopolitical risk (with even positive point estimates).

Given that geopolitical risk affects bank resilience variables (eg Phan et al. (2022)), we explore the impact of these on banks' lending responses. We examine the effect of important financial stability related variables such as the capital, profitability and liquidity of the lending bank. We find that better capitalised, more liquid, larger and more profitable banks are less sensitive to geopolitical risks in their borrowers.

Having established that geopolitical risk significantly influences banks' cross-border lending, we dig deeper into which broader factors related to geopolitics might be key drivers or amplifiers of this effect.

Using our text-based measures, we disaggregate geopolitical risk into key components - in particular geopolitical risks related to sanctions and geopolitical risks not related to sanctions - to examine how different components might affect bank lending. Our results suggest that banks have a more significant response to the sanctions element of geopolitical risk than other non-sanctions related factors. The latter continue to have significant effects, however, even when controlling for sanctions-related geopolitical risk.

We also explore the role of geopolitical distance and alignment and so contribute to the recent emerging literature on geopolitical financial fragmentation such as Aiyar et al. (2023) and Gopinath et al. (2025), which examines how geopolitical alignment is shaping capital flows. Because our dataset contains banks with a range of nationalities we are able to examine this issue at the bank-firm level and explore whether a bank's response to heightened geopolitical risk is higher when the firm it is lending to is from the same or ”opposing” bloc as determined by voting distance (Bailey et al. (2017)). We find that banks are more sensitive to an increase in geopolitical risk in firms in ”opposing” blocs.

Finally, in an extension, we move away from the firm-level and shed light on downstream transmission channels of geopolitical risk to macro variables using a more aggregate framework.We show that geopolitical risk depresses GDP and asset prices, which influences demand for cross-border lending. We also show that transmission varies depending on credit growth dynamics and also that the sanctions component of geopolitical risk has a larger impact on these aggregates and has heterogeneous impacts on lending in different currencies.

This paper proceeds as follows. Section 2 reviews the literature on the macro-financial impact of geopolitical risk and highlights our contributions to this literature. Section 3 presents our datasets for banks' large exposures and firm-level geopolitical risk, as well as aggregated data used to study transmission channels. Section 4 outlines our empirical strategy and baseline results, as well as sectoral and bank heterogeneities. Section 5 explores broader factors related to geoeconomics. Section 6 summarises our robustness checks. Section 7 illustrates transmission channels of geopolitical risk. Section 8 concludes.

2 Related literature

Much of the growing literature regarding geopolitical risk focuses on quantifying its macroeconomic impacts and transmission channels. In a comprehensive literature survey, Hodula et al. (2024) documents two principal channels through which geopolitical risk affects macro-financial stability. A financial channel, where heightened risk aversion lead to shifts in investment portfolio allocations and cross-border capital flows. And a real economy channel where both heightened uncertainty and disruption to global commodity markets and supply chains spill over to macroeconomic aggregates (Brignone et al. (2024), Caldara et al. (2024)).

A growing body of literature investigates the mechanisms by which banks adjust their operations in response to heightened geopolitical risk by examining banks' lending portfolios. Most closely related to our paper, Niepmann and Shen (2024) examine the effect of heightened geopolitical risk on US bank lending. They find that banks reduce cross-border lending in response to an increase in geopolitical risk but continue lending to those markets through their foreign affiliates. Banks also cut their domestic lending when geopolitical risk increases abroad, especially when they operate foreign affiliates in the country experiencing higher geopolitical risk. McQuade et al. (2025) examine bank lending in the EU in response to increased geopolitical risk at the bank portfolio level and find that more exposed banks cut their credit supply more generally, but cut it by more to firms operating in industries that relied more heavily on inputs from countries closely aligned with Russia. We add to these studies by examining banks' response to an increase in geopolitical risk at the individual borrower level –

by matching the change in geopolitical risk at borrower level to the lending relationship with its bank - and examining the bank's response to that individual risk. Our highly granular dataset means that we are able to explore multiple dimensions of the response such as the source of the geopolitical risk and the differing response across borrowing sectors and lender characteristics.

A few recent studies have begun to examine the effect of geopolitical risk on banks' resilience and performance. Phan et al. (2022) examine the effect of geopolitical risk on a sample of over 500 US banks from 1999 to 2019. After controlling for some bank specific and macroeconomic variables they find that heightened geopolitical risk is negatively associated with a number of measures of bank stability such as non-performing loans and return on assets. They also explore the impact of bank-specific variables and find that the effect of geopolitical risk on bank stability is stronger in banks with low profitability.[1] Behn et al. (2025) explore the relationship between bank stability and geopolitical risk using 120 years of data and find that a two standard deviation increase in a geopolitical risk index is associated with a decrease in the bank capital-to-asset ratio of around 0.2 percentage points. They highlight an important role for non-linearities – only very high geopolitical risk leads to a decline in bank capital levels — more moderate increases have no significant effect. We contribute to these studies by illustrating the linkages between geopolitical risk and financial stability. Cross-border lending to individual firms by better capitalised banks is insensitive to geopolitical risk. At the country-level, the effects of geopolitical risk on cross-border lending, macroeconomic aggregates and asset prices is greater than credit-to-GDP growth is higher.

De Haas et al. (2025) also examines the effect on different industries but examining syndicated lending during violent military conflicts and find that banks cut non-military lending in conflict zones. However, they increase military lending - as a result of increased demand. They also find that the geopolitical alignment of the home country is an important determinant: western banks increase their lending to miliary firms in eastern or neutrally aligned countries. We add to this work by providing a more general measure of geopolitical risk than armed conflicts and confirm that banks react to geopolitical risks in firms based in the defence sector by less compared to lending to

[1] Trinh and Tran (2024) obtain similar conclusions from a multi-country study.

firms in the financial sector, and also broaden their analysis on geopolitical alignment at the bank-firm level.

We contribute to the literature which shows important sectoral heterogeneities in the transmission of geopolitical risk, by examining the differing reaction by banks across sectors. Global trade and supply chains - and thus tradable industries - are particularly affected by geopolitical tensions. Rogers et al. (2024) finds that higher US-China tensions resulted in a reduction in bilateral trade flows, while Liu et al. (2024) find that Chinese exports are negatively affected when its trading partners are exposed to geopolitical risk. In addition, Hou et al. (2024) and Drobetza et al. (2021) find that higher geopolitical risk leads to a significant increase in trade costs, including shipping freight rates.A few studies show the importance of firm-level distinctions and market differentiation on geopolitical risk. Jung et al. (2021) use firm-level data, and find that heightened geopolitical risk reduces stock returns, and that the reductions in stock returns are greater especially for large firms, firms with a higher share of domestic investors, and for firms with a higher ratio of fixed assets to total assets. Federle et al. (2022) show, in the context of Russia's invasion of Ukraine, that exposure to the shock is an important determining factor, with higher negative returns the closer the firm is to Ukraine. We contribute to this literature by exploring how banks differentiate and respond to an individual firm-level metric of geopolitical risk.

Our paper also relates to the wider literature on the drivers of medium-term deglobalization and global economy fragmentation of capital and FDI flows. Aiyar et al. (2024) who examine greenfield FDI and finds a significant role for geopolitical alignment in determining the location of FDI; additionally they find that this 'friendshoring' has intensified since 2018 as trade tensions between the US and China resurged. Gopinath et al. (2025) find evidence that suggests a significant decline in trade, FDI, and portfolio flows between countries in geopolitically distant blocs since the onset of the war in Ukraine, relative to flows between countries in the same bloc. While most of this literature focuses on real economy investment and global supply chains some papers exist which examine financial portfolio flows. Converse and Malluci (2025) examine fund-level data on international bond funds' portfolio allocations and investor flows and find that increases in geopolitical risk spark financial fragmentation, with managers investing in fewer countries, holding portfolios that are more concentrated and tilted towards countries that are geopolitically aligned with the fund's home country. Our paper is related in that we examine how the bank's and the borrowing firm's geopolitical alignment affects how the bank responds to an increase in geopolitical risk at the firm-level.

3 Data

3.1 Large exposures dataset

Our main variable of interest is UK bank's cross-border lending to individual firms. We use the large exposures data developed by Covi et al. (2022), based on confidential large exposure supervisory reporting (COREP C.27-28 templates). This captures all UK banks' exposures above 10% of a bank's Tier 1 capital or above £260 million vis-'a-vis any counterparty located worldwide. We use quarterly data from 2015Q1 to 2024Q4.

We exclude borrowing firms based in the UK from the sample of economies considered for this analysis. This is in order for our regression results to focus specifically on how cross-border lending responds to geopolitical risk, as opposed to domestic bank lending. As of the most recent data, the nominal value of gross exposures to non-UK jurisdictions is around £2.5 trillion. This figure is comparable to the value of lending to domestic UK counterparties.

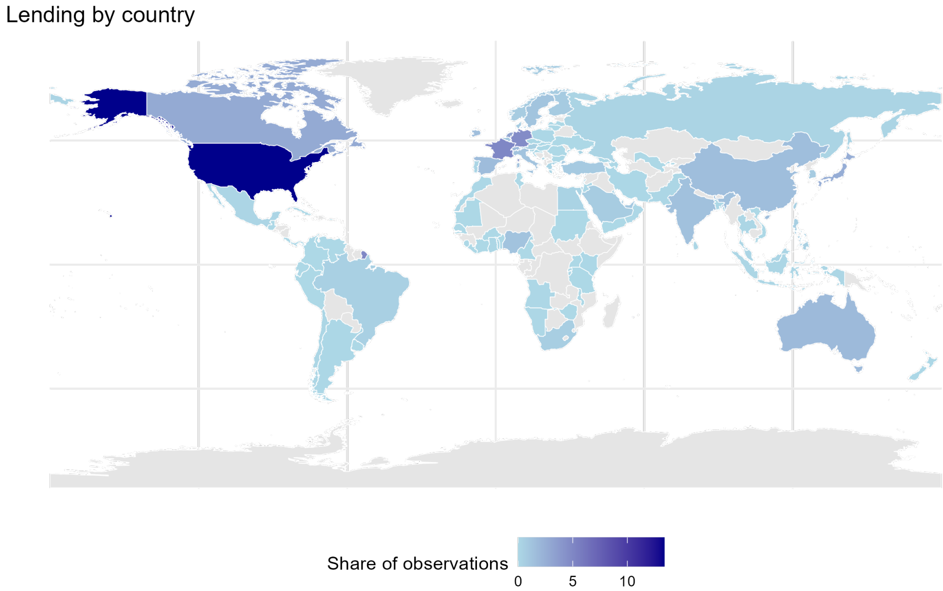
Our sample of banks consists over over 400 institutions, including: large UK banks, which participate in the Bank Capital Stress Test; smaller UK banks and building societies; and UK-based subsidiaries of banks globally headquartered in a foreign jurisdiction.

Figures 1a and 1b respectively chart the distribution of large exposures by the counterparty country and the nationality of lender. This shows that excluding the UK, the US is by far the largest destination with respect to both the destination of loans and the nationality of lenders.

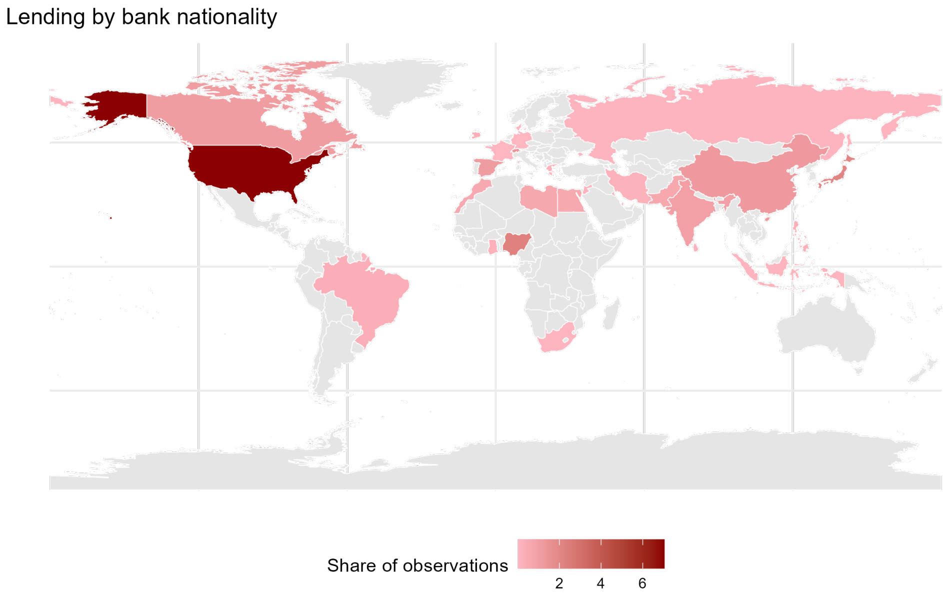
We use the same selection criteria as Covi et al. (2025) in order to focus on large banks with material cross-border lending. Namely, a bank must have, on average, at least two exposures reported per quarter, and these exposures should be reported for at

Figure 1: Comparison of lending patterns by country and by bank nationality

(a) Lending by country



(b) Lending by bank nationality



Notes: Shading denotes the share of total observations of lending by individual banks to individual firms in 2019Q4, excluding lending to the UK and lending by UK-headquarted banks.

least five quarters. As Covi et al. (2025) illustrate, this step has little effect on reducing the total number of exposure or their sterling amount, given the bulk of exposures is concentrated in larger banks.

We focus on quarterly percentage changes in gross exposures, at our desired level of aggregation. For robustness, we also consider how ”net” exposures vary in response to geopolitical risk. This series accounts for banks reducing their exposure to a counterparty, by obtaining collateral or insurance or other mechanisms. In aggregate, variation in growth rates of non-UK net exposures appears to mirror that of gross exposures (see Table 1).

One potential issue with calculating quarterly growth rates is a structural break in 2022Q2, related to banks' supervisory reporting. In our baseline specification, we thus exclude this quarter from the analysis. In addition, we check that the results are robust to the inclusion of this quarter noting that the use of time fixed effects - which also controls for time series variation in global factors such as oil prices - may to some extent mitigate the effect of the structural break.

Regarding sectoral variation, the large exposures dataset provides information on a counterparty's NACE code up to four digits, as well as the GICS sector to which a counterparty corresponds. NACE codes typically identify a sector by production, whereas GICS is more informative about final demand.

For our analysis, we re-group sectors in order to identify particular sectors of interest and aggregate across smaller sectors.[2] First, we regroup non-defence industries into: primary industries and mining (NACE codes A and B), as these are most directly energy-related; manufacturing (C); other secondary industries (D, E and F); financial services (K); public services (O); and all other private non-financial services. Table B1 gives an overview. Second, we identify industries relevant to defence from 4-digit NACE codes, as shown in in Table B2. These industries include public defence, as well as defence-releated manufacuturing such as arms, ammunition and aerospace. We extract defence-related industries from their original sectors to avoid double counting banks' exposures to these industries.

[2]This regrouping does not have a detrimental effect on the overall number of observations, due to the prevalence of smaller sectors for which only one bank lends to that sector in a given country.

The composition of UK banks' cross-border lending to these sector groups is shown in Table B3. We employ this broad sectoral allocation when we consider the robustness of our results to aggregating up from the firm-level to the country-sector level. When examining how geopolitical risk in individual firms affects banks' large exposures, we focus in on 4 sectors for which we have a sufficient number of firms and clear hypotheses on the effect of geopolitical risk: energy-related sectors, defence, manufacturing and financial lending.

Finally, we combine the large exposures data with bank-specific information, such as CET1 capital and profits. This allows us to compare how the impact of geopolitical risk on bank lending differs according to different bank characteristics.

3.2 Measuring geopolitical risk

The choice of how to measure geopolitical risk is of first order importance for our analysis. In order to assess how this affects UK bank lending, as measured by our large exposures dataset, we aim to exploit variation in geopolitical risk across a number of dimensions.

Arguably the most popular metric of geopolitical risk is the index developed by Caldara and Iacoviello (2022). This index is constructed using news searches from 10 major US- and UK-based newspapers. The index can be decomposed into acts versus threats, with a number of studies suggesting that the impact of geopolitical threats may differ notably from that of geopolitical acts. It is also disaggregated at the country-level, based on the juxtaposition of the relevant search terms with geographical terms.

The main shortcoming with this newspaper-based index, with regards to our empirical strategy, is that this does not provide variation beyond the country level. But the existing literature suggests that geopolitical risk differs in the way it impacts sectors and firms - a level of granularity which we are able to exploit with our large exposures dataset. We therefore build a firm-level metric of geopolitical risk to allow us to assess how firm-level variation in geopolitical risk affects firm-level variation in cross-border bank lending.

Specifically, we focus on an alternate metric of geopolitical risk based on using firms' earnings calls, which we obtain via the NL Analytics platform (Hassan et al.

(2025)). This index - originally developed also by Caldara and Iacoviello (2022) - is similar in spirit to the newspaper-based index, in that it fundamentally relies on text searches to identify geopolitical risk. The list of text searches (shown in Appendix A) is similar to, but more compact than, the full list of search terms used to construct the newspaper-based index. The index is available at a quarterly frequency from 2002Q1 onwards.

Crucially, this approach allows us to identify how geopolitical risk varies for individual firms across time. We can also aggregate the index to higher levels of granularity at the country or country-sector level. We identify country-level variation for around 80 different jurisdictions, based on the jurisdiction where a given firm is headquartered.[3] In addition, we can identify a firm's sector using information about the relevant SIC code. We match SIC codes to NACE codes, as outlined in Appendix B, in order to match sectoral variation in geopolitical risk with that of cross-country bank lending.Most importantly, the NL Analytics platform provides legal information about firms, namely their ISIN codes. Mapping ISIN codes to LEI codes, using information provided by the Global Legal Entity Identifier Foundation (2025), allows us to match firms in the NL Analytics and large exposures datasets, which in turn allows us to estimate how banks' lending to specific firms responds to geopolitical risk among those firms.

As Hassan et al. (2025) explain, there are a number of ways to measure variation in geopolitical risk from text searches in earnings calls in the NL Analytics platform. First, and most simply, it is possible to estimate the number of sentences in a given call that mention a given topic (in this case, geopolitics) divided by the total number of sentences (the "exposure" metric). Second, the authors create a comprehensive dictionary of terms related to risk, which ranges from words describing volatility (e.g. "variable", "variability"), to words indicating upside and downside potential (e.g. "chance", "prospect"). Combining this dictionary with search terms for geopolitical tension, the NL Analytics platform calculates the percentage of sentences in an earnings call that mention a synonym for risk or uncertainty, in the context of geopolitical tension (the "risk" measure). This measure reveals the level of concern firms express about specific

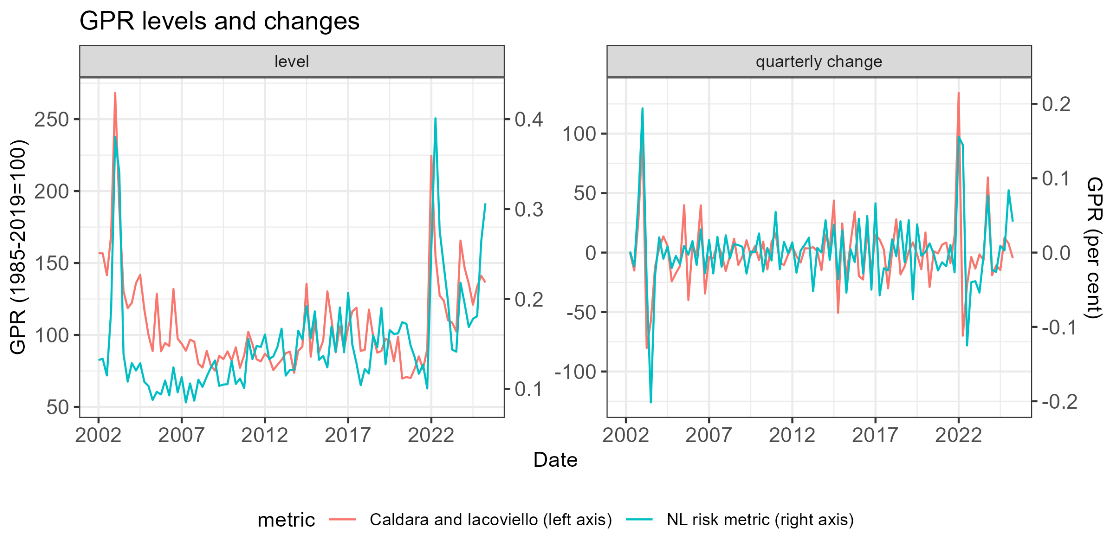
[3] In practice, global firms may operate in several jurisdictions that may be affected by geopolitical tension. However, information about where firms operate cannot be identified from the NL Analytics platform.

risks and may be most helpful to gauge potential economic impacts including the effects on cross-border lending. Third, the NL Analytics platform measures the tone of sentences related to gepolitical tensions, namely "negative" and "positive" tone sentences, as well as the net of these metrics (the "sentiment" metric).

Figure A1 compares the time series of these global geopolitical risk metrics, aggregated across all firms, with the quarterly averaged index of Caldara and Iacoviello (2022). These metrics are available from 2002Q1 onwards. Of these indices, the "risk" metric is most closely correlates with the Caldara and Iacoviello (2022) index, as shown in Figure 2. This metric follows movements in the Caldara and Iacoviello (2022) index during major geopolitical events such as the Iraq War in 2003H1 and Russia's invasion of Ukraine in 2022H1. This is unsurprising as the "risk" metric is most directly related to the level of concern firms express about geopolitical tension and may be most helpful to gauge potential economic impacts including the effects on cross-border lending.

Appendix A contains further details about the indexes including country and sectoral variation.

Figure 2: Geopolitical risk, levels and changes



3.3 Other data

While the data on large exposures and geopolitical risks are the key ingredients for our baseline analysis, we also collect supplementary data to support an extension section using more aggregate data of the effect on geopolitical risks on a wide range of macroeconomic outcomes.

We use this information to explore heterogeneity in the effect of geopolitical risk on bank lending at the country level and provide insight on possible transmission channels of geopolitical risk to bank lending.

The majority of macroeconomic variables we use is derived from the BIS website, including consumer prices, central bank policy rates, bilateral and effective exchange rates, residential property prices and credit data.

In addition, we use: real GDP data from the OECD quarterly national accounts for OECD economies and from national sources where these are not available. The list of datasets for each economy in our sample is explained in more detail in Table B4.

To obtain a country-level measure for bank lending we employ the BIS locational banking statistics. This gives a broader measure of country exposures compared to aggregating up our large exposures dataset by borrowers to the country level; it also allows to examine the currency dimension. Specifically, we obtain variation on cross-border inflows to our jurisdictions of interest from the rest of the world. The locational banking data provides both the level of banking exposures, as well as quarterly changes adjusted for exchange rate valuation effects. These data are available at a quarterly frequency over a much longer time horizon than the large exposures dataset, from the late 1970s for some jurisdictions.

4 Empirical strategy and baseline results

In this section, we start by discussing our main empirical framework and baseline results on the effects of geopolitical risk on the large firm-specific exposures of UK banks. We then explore heterogeneity across banks and sector. We explore factors the drivers of geopolitics and financial fragmentation in section 5 followed by outlining a number of robustness checks on our results in section 6.

4.1 Model specification

We run panel regressions of quarterly log changes in cross-country bank exposures, aggregated across a number of dimensions, on a metric of changes in geopolitical risk and a series of fixed effects.

Equation (1) sets out our main model specification, while Table 1 displays summary statistics for key variables:

$$\Delta EXP_{b,f,t} = \sum_{j=0}^{3} \beta_j \Delta GPR_{f,t-j} + f_{b,t} + f_{c,s,t} + f_f + \epsilon_{b,f,t} \quad (1)$$

Our main variable of interest $\Delta EXP_{b,f,t}$ is the quarterly log change in gross bank exposures by bank (b) to firm (f) at time (t). $\Delta GPR_{f,t}$ is the quarterly change of our preferred measure of geopolitical risk - the ″risk″ metric derived from firms earnings calls.[4] We include the contemporaneous geopolitical risk variable and three quarterly lags, which effectively illustrates how changes in geopolitical risk affect bank lending over a one year period. We winsorize data for both bank exposures and geopolitical risk at the 1% level, in order to avoid outliers distorting our results. Standard errors are clustered along the lines of the variation of our main explanatory variable (GPR), namely at the firm-time level in our preferred specification.

Table 1 also displays variation in quarterly log changes in ″net″ exposures, as well as the ″exposure″ and ″sentiment″ metrics from firms earnings calls.

Table 1: Summary statistics of key variables

	Mean	Median	SD	Min	Max	Obs.
Gross exposures (%)	-13.44	-2.68	49.65	-100.00	163.31	90470
Net exposures (%)	-12.28	-3.30	60.49	-100.00	277.54	79091
GPR risk (ppts)	-0.00	0.00	0.80	-2.00	2.00	118328
GPR sentiment (ppts)	-0.01	0.00	2.41	-11.00	11.00	118328
GPR exposure (ppts)	-0.11	0.00	6.22	-29.00	33.00	118328

Note: Summary statistics for country-level variables, expressed as quarterly changes from 2015Q1-2024Q4.

We gradually tighten the fixed effects to arrive at our preferred specification. f_f are firm-level fixed effects that control for unobserved heterogeneity across firms, while

[4] We explore the sentiment and exposure metrics based on call reports in the robustness section.

$f_{b,t}$ are joint bank-time fixed effects, that control for differences across banks and time. $f_{c,s,t}$ are joint country-sector-time fixed effects, which controls for time series variation across countries and sectors.

The latter includes global variation in geopolitical risk that may be driven by a combination of supply-side factors (such as commodity market disruption following Russia's invasion of Ukraine) and generic uncertainty manifesting as demand weakness. This tight fixed effect, therefore, removes the need for macroeconomic control variables and other time-varying measures controlling for supply and demand factors at country and sectoral levels.[5] This in turn allows us to identify the causal effect of changes in firm-level geopolitical risk to cross-country bank lending to those firms.

We cannot use firm-time fixed effects in this setting as this would exclude all firm-level variation in geopolitical risk. Rather, we cluster standard errors at the firm-time level for inference (given serial correlation in $\epsilon_{b,f,t}$).

We remove 2022Q2 from the sample of observations for the dependent variable, as the structural break in banks' large exposures reporting may distort estimated quarterly growth rates in that quarter.

4.2 The impact of geopolitical risk on cross-border lending to firms

Table 2 displays regression results from the firm-level regressions, building up fixed effects towards our preferred specification. In column (1), we use time, bank and firm fixed effects individually. The latter already nests variation across countries and sectors so we do not specify these fixed effects individually. Moving rightward across Table 2, we interact time fixed effects with specific groups, including countries and sectors.

We find that an increase in geopolitical risk reduces cross-border lending by UK banks to a given firm across all specifications. The estimated impact of geopolitical risk increases as we tighten the specification through the use of higher dimensional fixed effects. In our preferred specification (column (5)), where we deploy bank-sector-time and country-sector-time fixed effects, we find that a unit increase in geopolitical risk reduces cross-border bank lending by 5% up to one year. This effect is significant at the 5% level. Accounting for the variability of quarterly changes in geopolitical risk (as in

[5]The sample used for our baseline analysis is therefore not restricted to the countries listed in Table B4.

Table 2: Regression Results (Firm-level GPR)

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)	(5)
$dGPR_{f,t}$	-0.356	-0.543	-0.657	-0.576	-1.060*
	(0.504)	(0.540)	(0.547)	(0.572)	(0.601)
$dGPR_{f,t-1}$	-0.396	-0.354	-0.410	-0.596	-1.401*
	(0.617)	(0.663)	(0.668)	(0.693)	(0.734)
$dGPR_{f,t-2}$	-0.271	-0.410	-0.496	-0.607	-1.222
	(0.596)	(0.662)	(0.681)	(0.710)	(0.759)
$dGPR_{f,t-3}$	0.033	-0.361	-0.745	-0.956*	-1.359**
	(0.477)	(0.533)	(0.541)	(0.571)	(0.602)
Fixed effects	b,f,t	b-t,f	b-t,c-t,s-t,f	b-s-t,c-t,f	b-t,c-s-t,f
No. Observations	28961	25129	24240	22137	23454
Cum. GPR effect	-0.989	-1.668	-2.308	-2.735	-5.042
(p-value)	0.568	0.382	0.229	0.17	0.017
R^2	0.109	0.317	0.359	0.426	0.389
Adjusted R^2	0.089	0.195	0.217	0.232	0.228

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (1). The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Table 1), the implied impact of a one standard deviation increase in geopolitical risk is 4%, just over 1pp implied by column (5) of Table 2.

We also examine whether the results in Table 2 are borne out in more aggregated data. These results are shown in Table B5 in Appendix B: for the first two columns, bank lending and geopolitical risk is aggregated to the country level; for the remaining columns, we aggregate to the country-sector level. Across all specifications, we find that an increase in geopolitical risk results in a reduction in bank lending, which provides a degree of reassurance about the validity of our measures of geopolitical risks. This effect is only statistically significant in the tightest specification (column (5)) where we regress country-sector bank exposures on country-sector geopolitical risk and control for bank-sector-time and country-time fixed effects. In this specification, a unit increase in geopolitical risk reduces cross-border bank lending by around 7% over a one year period. This magnitude is similar to column (1), but involves a much tighter econometric specification.

Overall these results suggest that our micro-level estimates on the effect firm-specific geopolitical risk carry over to reductions in bank lending at the country and sectoral level. In the remainder of this section, we continue to focus the effects of firm-specific geopolitical risks which is our main focus.

4.3 Sectoral heterogeneity

The impact of geopolitical risk may vary depending on the sector the respective firm is based in. A number of papers suggest that the reaction to geopolitical risk could have a sectoral dimension; for example International Monetary Fund (2025) show a differing equity price response for different sectors including a positive response for the energy sector.

We therefore test the effect of an increase in geopolitical risk across different sectors, and modify equation 1 as follows:

$$\Delta EXP_{b,f,t} = \sum_{j=0}^{3} \beta_{1,j} GPR_{f,t-j} + \sum_{j=0}^{3} \beta_{2,j} GPR_{f,t-j} \times DUM_s + f_{b,t} + f_{c,s,t} + f_f + \epsilon_{b,f,t} \quad (2)$$

Where DUM_s is a dummy variable defined based on the sectors of interest discussed in section 3.

Table 3 displays regression results for a number of sectoral heterogeneities, where the dummy variable equals one if an observations pertains to a particular sector and zero otherwise. We include three tests at the bottom of the table. The *overall* estimated impact of geopolitical risk on lending to our sector of interest equals the sum of the geopolitical risk coefficients plus the dummy *interactions*, whereas the sum of the just the geopolitical risk coefficients denotes the impact on lending on the remaining sectors (*baseline*).

A number of results stand out. Focusing on the overall effects, we find that lending to firms in tradable sectors - manufacturing and especially financial services - appears most sensitive to an increase in geopolitical risk, as shown in columns (1) and (2). However, only for lending to the financial services sector do we find a negative interaction term of geopolitical risk with the sector dummy and a significantly negative overall effect.[6]

Financial services constitutes the majority of firms in the matched sample and is likely a key driver of the overall results (see Table B3). To that extent, the positive coefficients on the interaction terms for manufacturing reflects the fact this sector is slightly less affected by geopolitical risk than financial services. But in sum, lending to manufacturing falls in response to geopolitical risk. This is consistent with a number of studies (e.g. Rogers et al. (2024)) which find that geopolitical risk tends to depress trade in the affected country and disrupt supply chains, which in turn may discourage banks from lending to these industries.

In contrast, lending to firms in energy-related industries (column (3)) tends to increase in response to higher geopolitical risk, though the overall effect is not statistically significant. As Pinchetti (2024) finds, geopolitical risk is often associated with an increase in the prices and a reduction in output of energy goods. The net of these effects means that the profitability of these industries may be unaffected by - or may

[6]The fact that the interaction terms are not significant for the financial sector implies that we cannot conclusively say that lending to financial sector firms reacts differently to geopolitical risk compared to the average firm; but only for lending to financial sector firms do we find that geopolitical risk has overall a negative and significant effect.

increase in response to - an increase in geopolitical risk, with bank lending responding accordingly.

Similarly, lending to firms in defence-related industries (column (4)) increases in response to higher geopolitical risk. This effect again is not statistically significant, likely due to the limited volume of observations for defence-related industries (and high volatility of available observations). But the directional response is unsurprising, given that demand for defence-related outputs increases during times of high political tension. Similarly, De Haas et al. (2025) also finds that syndicated lending increases to military sectors in countries experiencing violent conflicts as a result of increased demand from that sector. Alternately, these findings may reflect substitution of lending away from some private sector activities - particularly tradable industries - towards public services that are more resilient to geopolitical tension.

Figure 3 visualises the results in Table 3. Namely, we compute linear combinations of the covariates and standard errors: each coloured line represents the mean cumulative impact of a one unit increase in geopolitical risk for a given sector over a given number of quarters, from $q = 0$ to $q = 3$; each coloured swathe representative the respective average standard error, equivalent to a 68% confidence interval. We also compare the sectoral results with the aggregate result from column (5) of Table 2.

Figure 3 illustrates that for manufacturing and financial services, an increase in geopolitical risk depresses cross-border lending to firms in those sectors over the course of one year, but is associated with an increase in lending to firms in energy- defence-related and industries. For financial services, the aggregate effect is statistically significant up to one year, while the 68% confidence intervals for manufacturing fall below zero at $q = 1$ and $q = 2$. However, the aggregate and sector-specific confidence intervals overlap, suggesting the results for these sectors are not significantly different from the aggregate. Also, the results for energy- defence-related and industries are not statistically significant in absolute.

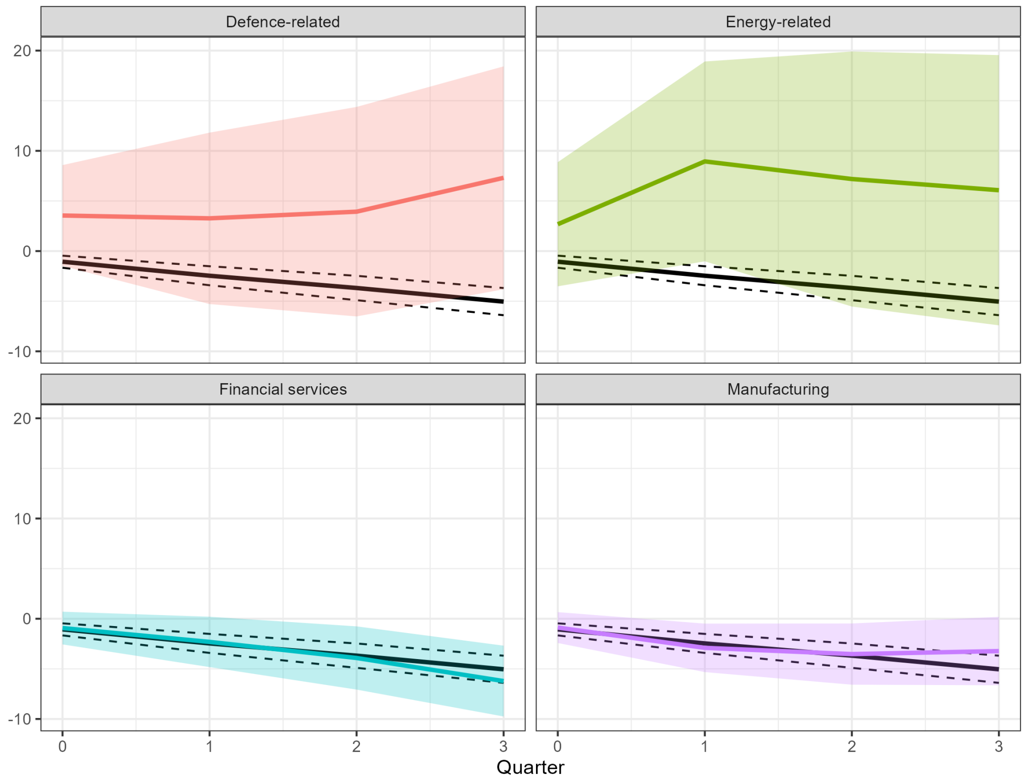
Table B6 in Appendix B aims to replicate this result in the country-sector panel, namely lending across sectors and lending between blocs. The country-sector panel is less heavily influenced by the financial services sector, compared to the firm-level panel, as this constitutes only one sector rather than the majority of firm-level observations.

Table 3: Sector heterogeneity

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR_{f,t}$	-1.088	-1.207	-1.075*	-1.101*
	(0.691)	(1.027)	(0.604)	(0.605)
$dGPR_{f,t-1}$	-1.251	-1.386	-1.439*	-1.417*
	(0.839)	(1.187)	(0.737)	(0.737)
$dGPR_{f,t-2}$	-1.390	-0.510	-1.217	-1.245
	(0.885)	(1.159)	(0.762)	(0.763)
$dGPR_{f,t-3}$	-1.798**	0.592	-1.364**	-1.402**
	(0.701)	(0.986)	(0.605)	(0.606)
$dGPR_{f,t} * DUM_s$	0.209	0.279	3.753	4.649
	(1.374)	(1.266)	(6.161)	(4.991)
$dGPR_{f,t-1} * DUM_s$	-0.772	0.004	7.707	1.135
	(1.664)	(1.495)	(7.776)	(6.875)
$dGPR_{f,t-2} * DUM_s$	0.767	-1.093	-0.540	1.910
	(1.639)	(1.513)	(7.868)	(5.960)
$dGPR_{f,t-3} * DUM_s$	2.097	-2.896**	0.247	4.781
	(1.354)	(1.248)	(4.412)	(3.745)
Sector	Manufacturing	Fin. services	Energy	Defence
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f
No. Observations	23450	23450	23450	23450
Cum. GPR baseline	-5.527	-2.512	-5.094	-5.165
(p-value)	0.023	0.452	0.016	0.015
Cum. GPR interaction	2.3	-3.706	11.167	12.475
(p-value)	0.629	0.387	0.62	0.33
Cum. GPR overall	-3.227	-6.217	6.072	7.31
(p-value)	0.43	0.021	0.787	0.627
R^2	0.389	0.389	0.389	0.389
Adjusted R^2	0.228	0.228	0.228	0.228

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. This table reports the estimation results for equation (2). The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Figure 3: Sector heterogeneity: cumulative effects



Notes: Coloured lines denote sector-specific mean estimates, black lines denote aggregate mean estimates. Mean results are computed as $\sum_{i=1}^{N} \mathbf{B}_i$, where N is the total number of relevant slope coefficients $\mathbf{B}_i$. Shaded coloured areas and dotted black lines denote 68% confidence interval around mean estimates for sector-specific and aggregate mean estimates respectively, with standard errors computed as $\sqrt{\sum_{i=1}^{N} \mathbf{SE}_i^2}$.

Nonetheless, Table B6 confirms that tradable sectors are most affected by geopolitical risk - albeit with a much larger estimated negative response for manufacturing - and that lending to energy- and defence-related industries increases in response to geopolitical risk.

4.4 Bank heterogeneity

Columns (1) to (4) of Table 4 interact geopolitical risk with a given bank's liquidity coverage ratio (LCR), CET1 capital ratio (share of risk weighted assets), profitability (total profits as a share of assets) and size (in total assets) respectively. Specifically, we interact geopolitical risk with a dummy variable that equals one when the value of a given characteristic is in the top third of a given characteristic.[7] The results - and in particular the sum of the baseline and interaction terms - suggest that better capitalised banks appear less sensitive to changes in the geopolitical risk environment over a one-year horizon, suggesting they may be more resilient to rising geopolitical tensions. A test of the baseline and interaction terms give a small positive point estimate for the effect of firm-specific geopolitical risk on banks firm-level large exposures. Vice versa, for banks within the lower two-thirds of the distribution of the respective characteristics, the baseline results indicate significant transmission of geopolitical risk to exposures.

Larger firm size is also associated with reduced responsiveness to geopolitical risk, suggesting these institutions are better able to withstand geopolitical tensions, though this result is not statistically significant. A bank's LCR or profit ratio appears to have little effect on how its lending responds to geopolitical risk.[8]

As we sectoral heterogeneities, we visualise our result for bank heterogeneities in Figure 4. The black lines and shaded areas illustrate the baseline results, for which $D_{b,t} = 0$, while the red lines and shaded areas illustrate the results for which $D_{b,t} = 1$. Most strikingly, an increase in geopolitical risk has near-zero effect on cross-border lending by banks where CET1 ratios are above the 68$^{\text{th}}$ percentile. These banks have a CET1 ratio in excess of 18%, but this can be much higher in some instances. By contrast, cross-border lending by other banks is slightly more sensitive to geopoolitical risk than the sample average. This result is less pronounced for other characteristics, however. More profitable banks appear to cut back lending more steeply than less profitable banks over the first two quarters after an increase in geopolitical risk, though the difference across thresholds is not statistically significant.

[7] Data points are winsorized at the 1$^{\text{st}}$ percentile to eliminate extreme observations, that possibly arise due to poor data reporting by banks.

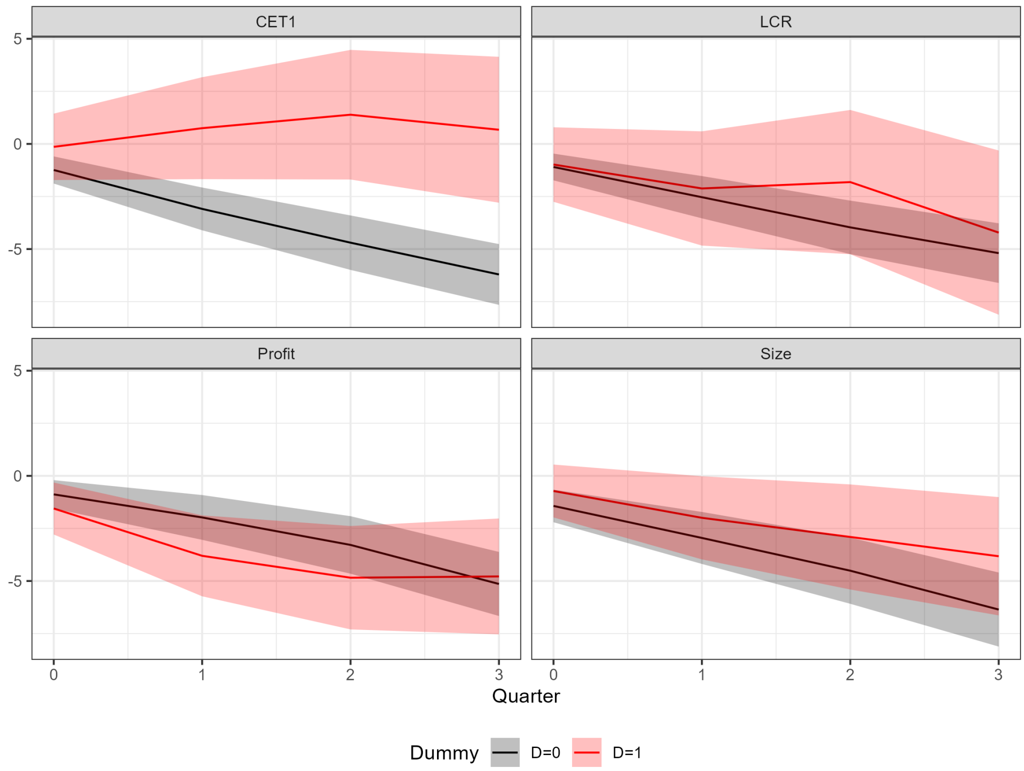
[8] These results are directionally consistent with interacting geopolitical risk with the continuous time series of the respective bank variables.

Table 4: Bank heterogeneity

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR_{f,t}$	-1.097*	-1.240*	-0.881	-1.430*
	(0.635)	(0.645)	(0.677)	(0.775)
$dGPR_{f,t-1}$	-1.437*	-1.850**	-1.096	-1.522
	(0.778)	(0.786)	(0.821)	(0.962)
$dGPR_{f,t-2}$	-1.435*	-1.607**	-1.307	-1.558
	(0.782)	(0.802)	(0.858)	(0.973)
$dGPR_{f,t-3}$	-1.225*	-1.511**	-1.856***	-1.847**
	(0.626)	(0.643)	(0.672)	(0.791)
$dGPR_{f,t} * DUM_{b,t}$	0.116	1.101	-0.673	0.711
	(1.654)	(1.441)	(1.033)	(0.989)
$dGPR_{f,t-1} * DUM_{b,t}$	0.299	2.738*	-1.153	0.246
	(1.907)	(1.663)	(1.227)	(1.185)
$dGPR_{f,t-2} * DUM_{b,t}$	1.738	2.247	0.266	0.648
	(1.944)	(1.727)	(1.266)	(1.177)
$dGPR_{f,t-3} * DUM_{b,t}$	-1.176	0.796	1.917*	0.930
	(1.758)	(1.457)	(1.046)	(1.022)
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f
Interaction	$\text{LCR}_{b,t}$	$\text{CET1}_{b,t}$	$\text{Profit}_{b,t}$	$\text{Size}_{b,t}$
No. Observations	23450	23450	23450	23450
Cum. GPR baseline	-5.194	-6.208	-5.14	-6.358
(p-value)	0.019	0.006	0.031	0.021
Cum. GPR interaction	0.977	6.882	0.358	2.535
(p-value)	0.856	0.147	0.92	0.454
Cum. GPR overall	-4.217	0.674	-4.783	-3.823
(p-value)	0.418	0.881	0.137	0.15
R^2	0.389	0.389	0.389	0.389
Adjusted R^2	0.228	0.228	0.228	0.228

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (2) but replacing the sectoral interactions with bank-time specific balance sheet variables. The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Figure 4: Bank heterogeneity: cumulative effects



Notes: Shaded areas denote 68% confidence interval around mean estimates. Mean results are computed as $\sum_{i=1}^{N} \mathbf{B}_i$, where N is the total number of relevant slope coefficients $\mathbf{B}_i$. Standard errors are computed as $\sqrt{\sum_{i=1}^{N} \mathbf{SE}_i^2}$.

5 Geopolitics and financial fragmentation

Our baseline results suggest there may be a role for geopolitics as a contributor to financial fragmentation via its role in reducing cross-border lending, even at the level of long-established bank-firm relationships.[9] In this section, we dig deeper into which broader factors related to geopolitics might be key drivers or amplifiers of this effect.

[9]In section 6 we show that domestic lending is less sensitive to geopolitical risk than cross-border lending.

5.1 Components of geopolitical risk

We start by focusing on the the sanctions component of our index of geopolitical risk. To do so, we compile a parsimonious dictionary of search terms relevant to sanctions, shown in Apppendix A. Our search terms include sanctioning authorities (e.g. OFAC), sanctioned jurisdictions (e.g. Russia, Venezuela), or types of sanctions (e.g. asset freeze, embargo). We then extract the "risk" index from firms earnings calls using the intersection of sanctions search terms and geopolitical risk search terms we used before. This approach of using overlapping search terms allows us the extract the component of geopolitical risk that is driven by sanctions.

There may be two main factors, which are difficult to disentangle, that could drive firm-specific geopolitical risks related to sanctions. First, firms might not geopolitical risk related to sanctions if they themselves are impacted by sanctions. Second, firms might note such risks in their supply chains or financial counter-parties or in the broader economy with implications for their business.

Figure 5: Components of geopolitical risk

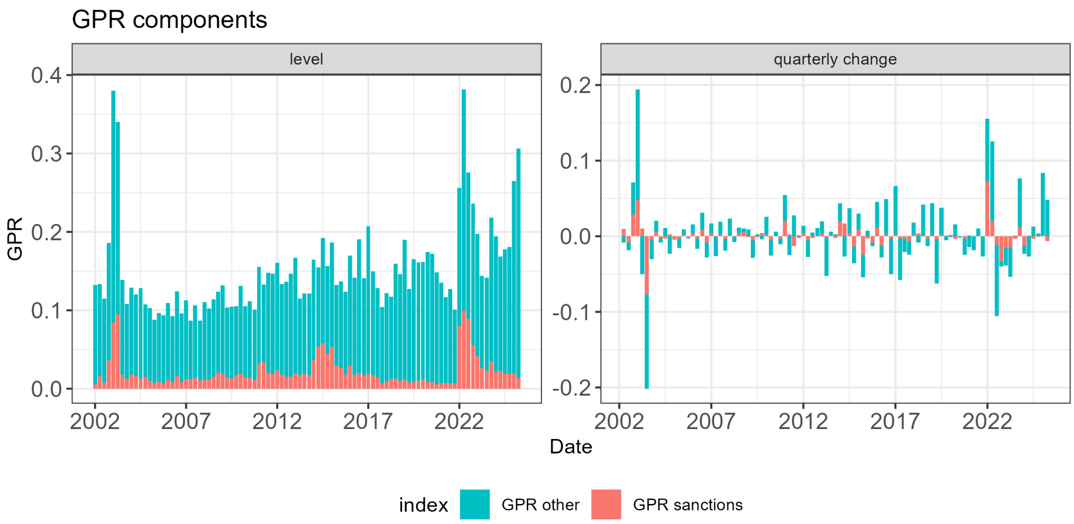


Figure 5 decomposes the aggregate geopolitical risk index (from earnings calls) into sanctions versus the remaining component. This shows that sanctions drives a substantial component of overall fluctuations in geopolitical risk. In particular, the blue bars widen during 2014 and 2022 after western nations imposed sanctions on Russia. By contrast, more recent spikes in the geopolitical risk index, such as following the start of the recent Israel-Gaza conflict, are not associated with as steep an increase in sanction-related geopolitical risk.

Table 5 displays regression results for the impact of different components of geopolitical risk on bank lending. Column (1) displays the results of the sanctions component, while Column (2) displays the results of both components. These estimates, also visualised in the left panel of Figure 6, show that bank lending is both responsive to the sanctions component of geopolitical risk as well as the residual component. The former has a materially larger point estimate than the latter, though both estimates are statistically significant.[10]

A key rationale for this result may be that banks are much more reluctant to lend to firms, as well as to sectors and countries more broadly, where their assets may be seized if sanctions are imposed. This is particularly true of firms in the financial services sector, shown in columns (3) and (4) of Table 5 and the right panel of Figure 6. We find that cross-border lending to these firms is most sensitive to geopolitical risk, as sanctions often involve restrictions on financial relationships or on trade flows linked to these relationships.

5.2 Geopolitical blocs

We combine information about the parent nationality of the banks in the large exposures dataset with the countries hosting the firms they lent to in order to test hypotheses about ”friendshoring” in response to geopolitical risk. We group countries into US- and China-led blocs, following Bailey et al. (2017)'s approach using on UN voting data, and define dummy variables based on bank-nationality and counterparty country pairs to identify within and between bloc lending. The results are shown in 6. Columns (1) and (4) show lending within the US-led and China-led blocs respectively, while columns (2) and (3) show lending between the different blocs.

Figure 7 displays a snapshot of lending between geopolitical blocs, in terms of the number of observations of bank-firm pairs (with lending to UK firms excluded). This shows that the majority of observations in the dataset constitute lending by ”US” bloc

[10] A test confirms that there is no significant difference between the two factors at the 10% level.

Table 5: Sanctions versus other components

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR^{sanc}_{f,t}$	-2.192	-2.128	-2.180	-1.828
	(1.629)	(1.638)	(2.337)	(2.371)
$dGPR^{sanc}_{f,t-1}$	-4.604**	-4.439**	-6.020**	-5.444*
	(1.972)	(2.000)	(2.848)	(2.927)
$dGPR^{sanc}_{f,t-2}$	-2.874	-2.763	-2.730	-2.466
	(1.931)	(1.943)	(2.949)	(2.986)
$dGPR^{sanc}_{f,t-3}$	-3.147**	-3.247**	-3.906*	-4.031*
	(1.558)	(1.556)	(2.356)	(2.363)
$dGPR^{other}_{f,t}$		-0.960		-0.940
		(0.638)		(0.797)
$dGPR^{other}_{f,t-1}$		-0.955		-1.026
		(0.793)		(1.005)
$dGPR^{other}_{f,t-2}$		-0.964		-1.561
		(0.816)		(1.048)
$dGPR^{other}_{f,t-3}$		-1.006		-1.952**
		(0.665)		(0.843)
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-t,f	b-t,c-t,f
Sample	All obs.	All obs.	Fin. services	Fin. services
No. Observations	23454	23450	13349	13345
Cum. GPR sanctions	-12.817	-12.577	-14.836	-13.769
(p-value)	0.018	0.021	0.065	0.092
Cum. GPR other		-3.885		-5.479
(p-value)		0.093		0.064
R^2	0.389	0.389	0.437	0.437
Adjusted R^2	0.228	0.228	0.246	0.246

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (1) but disaggregating the GPR measure into GPR related to sanctions vs other factors. The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Figure 6: Sanctions versus other components: cumulative effects

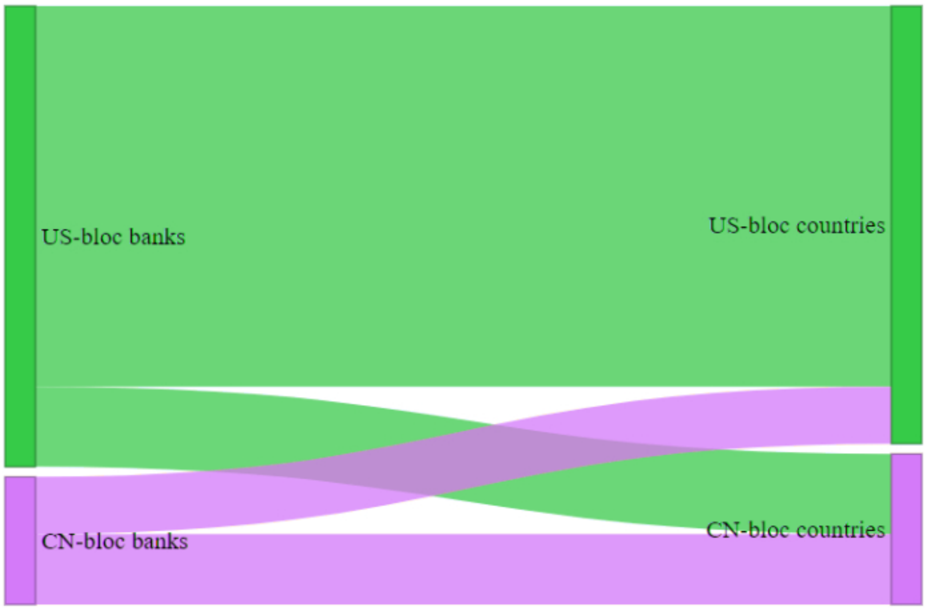
Notes: Shaded areas denote 68% confidence interval around mean estimates. Mean results are computed as $\sum_{i=1}^{N} \mathbf{B}_i$, where N is the total number of relevant slope coefficients $\mathbf{B}_i$. Standard errors are computed as $\sqrt{\sum_{i=1}^{N} \mathbf{SE}_i^2}$.

nationality banks to firms in that same bloc. The remaining three flows - lending by "China" bloc nationality banks to "China" bloc firms and lending between banks and firms from opposing blocs - consistute a roughly similar share of of total observations.

The regression results show in Table 6 are mixed. In terms of the point estimates of the interaction terms and overall cumulative effects (found at the bottom of the table), the results suggest larger negative effects of lending outside one's own bloc compared to lending within the same bloc. However, in both cases the effect does not differ significantly from the average effect (with interaction terms being insignificant). In contrast, bank lending within the "US" bloc still reacts to geopolitical risk in borrowing firms with the fact being somewhat muted compared to the average but still significant at the 10% level. Finally, there is evidence that bank lending within the "China" bloc does, if anything, increases when faced with geopolitical risks in borrowing firms (though this effect is not statistically significant).

We cross-check these results with a sample which includes only financial services firms, show in Table 7, as lending to these firms tends to be most responsive to geopolit-

Figure 7: Lending flows between geopolitical blocs



Notes: Size of flows proportional to the share of total observations of lending by individual banks to individual firms in 2019Q4, excluding lending to the UK.

ical risk. These results are directionally consistent with the estimates in Table 6, in that bank lending to firms within the same geopolitical bloc (columns (1) and (4)) tends to be less sensitive to an an increase in geopolitical tension than lending to firms in the opposite bloc (columns (2) and (3)), though the overall cumulative impacts. Columns (1) and (4) also show that within-bloc lending to financial services firms is more sensitive to geopolitical risk compared to the sample with all firms.

Taken together, this evidence points to banks reallocating their exposures when geopolitical tensions rise, shifting portfolios to countries within their respective bloc (at least in the case of the ”China” bloc). This is in line with Aiyar et al. (2024) and Gopinath et al. (2025) who find similar results for FDI and portfolio flows; our results suggest a similar ”friendshoring” pattern for cross-border bank lending.

Table 6: Flows between blocs

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR_{f,t}$	-1.138	-1.057*	-0.974	-1.057*
	(0.808)	(0.601)	(0.609)	(0.602)
$dGPR_{f,t-1}$	-1.732*	-1.355*	-1.422*	-1.384*
	(0.957)	(0.733)	(0.743)	(0.736)
$dGPR_{f,t-2}$	-1.350	-1.201	-1.296*	-1.254*
	(1.002)	(0.759)	(0.766)	(0.760)
$dGPR_{f,t-3}$	-1.461*	-1.336**	-1.346**	-1.375**
	(0.790)	(0.602)	(0.610)	(0.603)
$dGPR_{f,t} * DUM_{b,c}$	0.135	4.861	-4.579	2.768
	(0.872)	(7.831)	(4.553)	(10.064)
$dGPR_{f,t-1} * DUM_{b,c}$	0.578	-15.364*	1.173	-7.488
	(0.998)	(8.616)	(4.980)	(9.292)
$dGPR_{f,t-2} * DUM_{b,c}$	0.224	-1.909	3.384	11.994
	(1.018)	(9.053)	(5.189)	(11.407)
$dGPR_{f,t-3} * DUM_{b,c}$	0.184	-7.705	-0.589	3.366
	(0.852)	(8.512)	(4.130)	(12.099)
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f
Interaction	$\text{US}_b \rightarrow US_f$	$\text{US}_b \rightarrow CN_f$	$\text{CN}_b \rightarrow US_f$	$\text{CN}_b \rightarrow CN_f$
No. Observations	23449	23449	23449	23449
Cum. GPR baseline	-5.681	-4.949	-5.039	-5.071
(p-value)	0.041	0.019	0.018	0.017
Cum. GPR interaction	1.121	-20.116	-0.61	10.64
(p-value)	0.698	0.463	0.964	0.749
Cum. GPR overall	-4.561	-25.065	-5.649	5.569
(p-value)	0.054	0.361	0.676	0.867
R^2	0.389	0.390	0.390	0.390
Adjusted R^2	0.228	0.229	0.229	0.229

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (2) and replacing the sectoral interactions with a variable measuring whether flows are within or between the respective geopolitical blocs. The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Table 7: Flows between blocs (financial services only)

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR_{f,t}$	-0.662	-0.928	-0.784	-0.928
	(0.953)	(0.759)	(0.774)	(0.761)
$dGPR_{f,t-1}$	-1.657	-1.419	-1.440	-1.444
	(1.124)	(0.950)	(0.966)	(0.956)
$dGPR_{f,t-2}$	-2.038*	-1.686*	-1.788*	-1.704*
	(1.185)	(0.997)	(1.010)	(1.000)
$dGPR_{f,t-3}$	-2.031**	-2.272***	-2.295***	-2.301***
	(0.938)	(0.778)	(0.790)	(0.781)
$dGPR_{f,t} * DUM_{b,c}$	-0.572	7.302	-5.998	4.559
	(1.074)	(9.339)	(5.351)	(10.970)
$dGPR_{f,t-1} * DUM_{b,c}$	0.379	-14.622	-1.386	-8.729
	(1.222)	(11.721)	(5.809)	(10.377)
$dGPR_{f,t-2} * DUM_{b,c}$	0.737	10.360	3.897	7.657
	(1.248)	(10.891)	(5.900)	(12.330)
$dGPR_{f,t-3} * DUM_{b,c}$	-0.560	-7.074	0.064	-1.862
	(1.056)	(11.970)	(4.674)	(12.919)
Fixed effects	b*t, c^*s^*t, f	b*t, c^*s^*t, f	b*t, c^*s^*t, f	b*t, c^*s^*t, f
Interaction	$\text{US}_b \rightarrow US_f$	$\text{US}_b \rightarrow CN_f$	$\text{CN}_b \rightarrow US_f$	$\text{CN}_b \rightarrow CN_f$
No. Observations	13344	13344	13344	13344
Cum. GPR baseline	-6.389	-6.305	-6.307	-6.377
(p-value)	0.051	0.022	0.024	0.021
Cum. GPR interaction	-0.015	-4.033	-3.422	1.626
(p-value)	0.997	0.912	0.826	0.962
Cum. GPR overall	-6.404	-10.338	-9.729	-4.751
(p-value)	0.051	0.776	0.525	0.889
R^2	0.437	0.437	0.438	0.438
Adjusted R^2	0.246	0.247	0.247	0.247

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (2) and replacing the sectoral interactions with a variable measuring whether flows are within or between the respective geopolitical blocs. The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

6 Robustness

We explore a number of robustness checks around our model specification. These are summarized in Appendix A.

Our baseline results are robust across a number of dimensions, as shown in Table B7. These include: replacing gross exposures with net exposures (column (1)); not winsorizing the changes in geopolitical risk indices (column (2)); retaining 2022Q2 in the sample of observations (column (3)); and controlling for the lagged dependent variable (column (4)). With the exception of column (1), all the other sensitivities are statistically significant, while the greater p-value of column (1) may reflect the greater variability of the net exposures data.

Table B8 assesses the response of cross-border lending to the "exposure" and "sentiment" geopolitical risk metrics provided by the NL Analytics platform. We find that in general, these indices do not have a significant effect on cross-border lending. This is also true when we restrict the sample to just financial services, the sector most sensitive to geopolitical risk. This suggests that banks' perception of risks facing a given firm, on account of the geopolitical environment, is the main driver of their lending decisions. By contrast, other studies find that "sentiment" is more relevant when explaining how geopolitical risk affects asset prices (Culver et al. (2025)).

Finally, Table B9 introduces lending to UK-based firms into the sample of observations, and tests a number of heterogeneities around this. Column (1) shows that domestic lending is less sensitive to geopolitical risk than cross-border lending. Column (2) shows that lending by banks to firms in their home country appears less sensitive to geopolitical risk than other lending. However, this result is mostly explained by UK headquartered banks' lending to UK-based firms - a pure domestic loan (Column (3)) - whereas banks' lending to their home country for non-UK jursidictions is not statistically different from the sample average.

On balance, these robustness checks provide reassurance about our result that geopolitical risk depresses cross-border bank lending, though this highlights sensitivities associated with the granular dataset.

7 Macroeconomic transmission

In this section, we shed light on downstream transmission channels of country-level geopolitical risk to cross-country bank lending, via macro-financial variables. For this analysis, we deploy a more aggregate framework, which also allows us to cross-check our analysis in the firm-level dimension.

Specifically, we use local projections to investigate the dynamic properties of the transmission of geopolitical risk via macroeconomic outcomes. Our regression specification is as follows:

$$Y_{c,t+h} - Y_{c,t-1} = \alpha + \beta GPR_{c,t} + \gamma X_{c,t-1} + f_c + f_t + \epsilon_{c,t} \tag{3}$$

Where $Y_{c,t+h} - X_{c,t-1}$ is the change in our variable of interest for country c between period t+h and period t-1. We investigate how geopolitical risks transmit up to 12 quarters. $GPR_{c,t}$ is country-level geopolitical risk, measured by earnings calls, winsorized at the 1st percentile. $X_{c,t-1}$ is a vector of control variables, including two lags of the levels of each variable of interest, including our measure of geopolitical risk.[11] We also include country and time fixed effects.

To explore heterogeneities, we use a state-dependent local projection framework, as outlined by Gonçalves et al. (2024). Specifically, we interact geopolitical risk with dummy variables as follows:

$$\begin{aligned} Y_{c,t+h} - Y_{c,t-1} = \alpha + \beta_1 GPR_{c,t} Z_{c,t} + & \beta_0 GPR_{c,t}(1 - Z_{c,t}) \\ & + \gamma X_{c,t-1} + f_c + f_t + \epsilon_{c,t} \end{aligned} \tag{4}$$

β_1 is the estimated impact of geopolitical risk when the dummy variable $Z_{c,t}$ equals one, while β_0 is the estimated impact when $Z_{c,t}$ equals zero.

Our approach using local projections requires a longer period time than is available in our large exposures dataset. For bank lending, we source data on total cross-border inflows to a given jurisdiction from the BIS locational banking statistics, which we ad-

[11] This regression specification is asymptotically equivalent to a structural vector autoregression model, identified using a Cholesky decomposition where geopolitical risk can affect all variables contemporaneously.

just for exchange rate valuation effects.[12] We discuss other macro data in section 3.3. Given the data availability of geopolitical risk from earnings calls, the sample of observations spans 2002Q1 to 2024Q4. Summary statistics of country-level variables over this period are shown in Table 8.

Table 8: Summary statistics for macroeconomic variables

	Mean	Median	SD	Min	Max	Obs.
GPR risk (ppts)	0.00	0.00	0.29	-2.00	2.00	3727
Real GDP (log)	0.67	0.72	2.20	-25.85	21.87	4878
CPI (log)	0.75	0.60	1.06	-3.52	9.84	5127
Policy rate (ppts)	-0.00	0.00	0.63	-12.54	8.33	4952
Effective exchange rate (log)	-0.01	0.12	2.69	-27.43	31.34	5261
Equity prices (log)	1.48	2.42	11.89	-168.05	78.72	4960
House prices (log)	1.24	1.17	2.77	-26.22	23.91	4745
Locational claims (log)	1.18	0.89	6.98	-57.37	48.23	5260

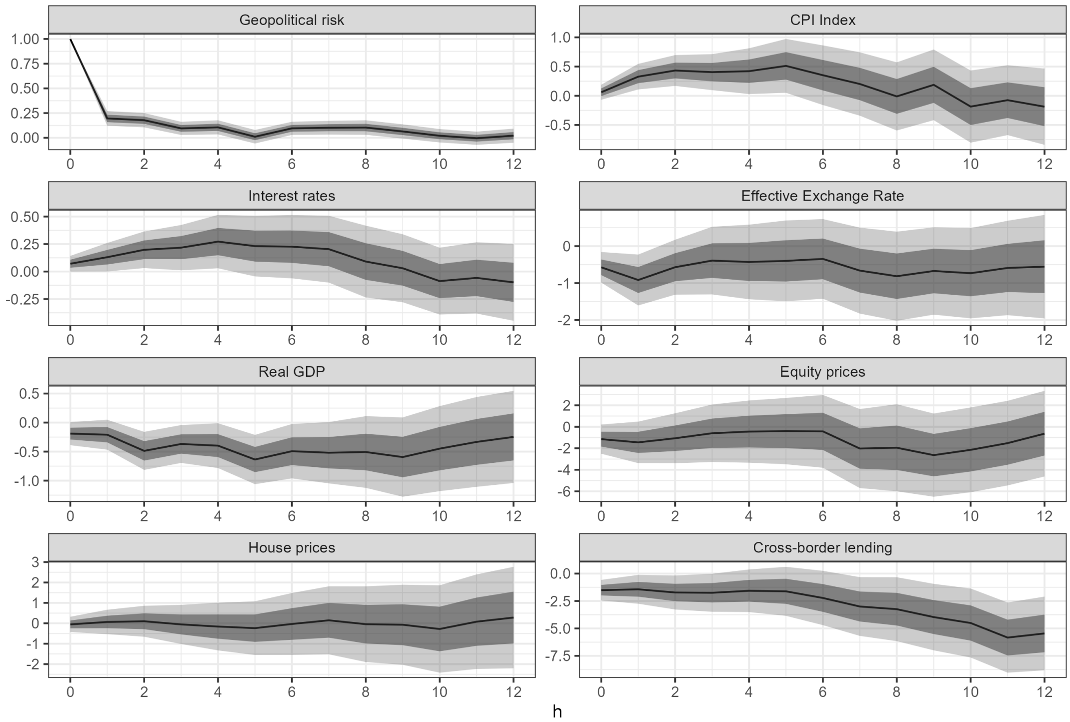
Note: Summary statistics for country-level variables, expressed as quarterly changes from 2002Q1-2024Q4.

Figure 8 shows our baseline local projection results based on the non-interacted equation (3). This shows that a unit increase in country-level geopolitical risk reduces cross-border bank lending by around 1.5% on impact. This impact builds to 7.5% after three years. From the summary statistics in Table Table 8, this implies a one standard increase in geopolitical risk reduces cross-border bank lending by 2.8%, a slightly smaller impact than implied by the results in Table 2 from the large exposures dataset. The local projection of geopolitical risk indicates only limited persistence after the shock crystallizes.

Regarding other variables, real GDP and and equity prices fall materially after the geopolitical risk stress crystallises. This suggests that cross-border bank lending responds significantly to the macroeconomic environment, as income and wealth effects influence demand for lending. House prices are not significantly affected by geopolitical risk, however. Nominal effective exchange rates depreciates on impact, though this effect subsides after one year. CPI and interest rates increase slightly on impact, which could be due to monetary policymakers looking to offset inflationary effects of

[12] We obtain a levels series of the valuation-adjusted data by combining the starting level of the unadjusted levels data with the cumulative sum of the valuation-adjusted quarterly changes. We can then estimate quarterly log changes of this constructed levels series.

Figure 8: Local projections of geopolitical risk



Notes: Dark shaded areas denote 68% confidence interval around mean estimates. Light shaded areas denote 95% confidence interval.

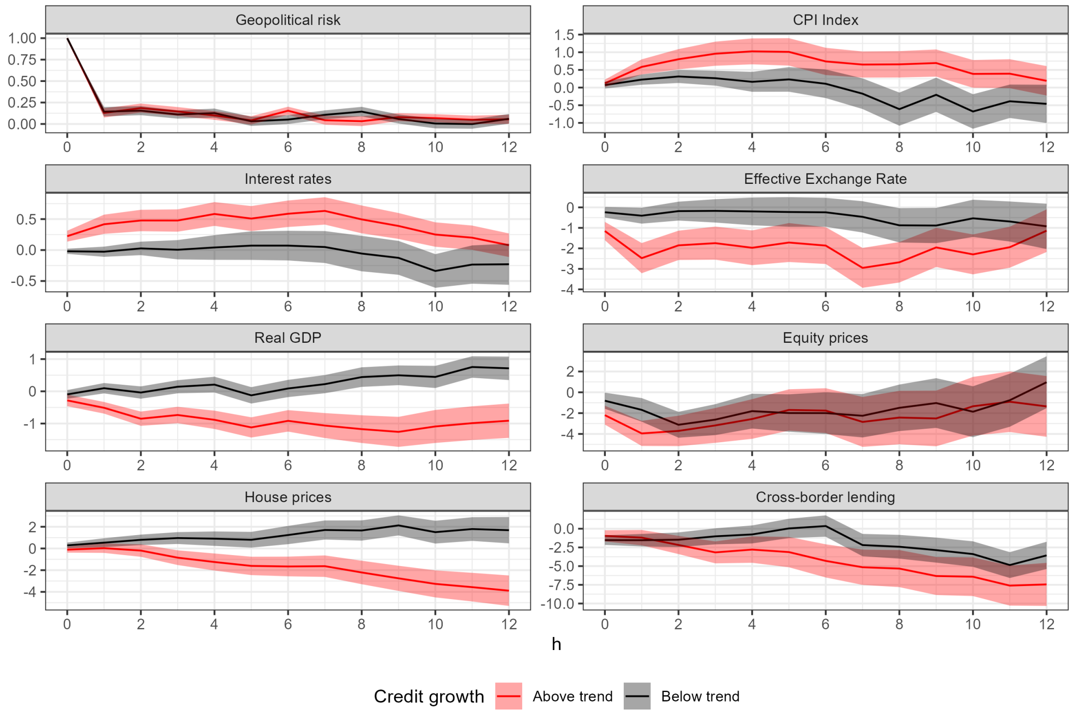
exchange rate depreciation.

We explore three sets of heterogenities in the local projections using equation (4). First, in Figure 9, we explore transmission in geopolitical risk when credit growth is high (red lines) versus low (blue lines). We define high credit growth - indicative of greater financial stability risks - as the three-year change in the credit-to-GDP ratio of a given country in a given quarter being above the 68th percentile of the full sample.

This shows that the fall in cross-border bank lending is materially greater under high credit growth. The main channel appears to be business cycle dynamics: the fall in real GDP is more pronounced under a credit boom; also house prices falls significantly, unlike the impulse responses in 8. In addition, exchange rate depreciation is larger and more persistent under high credit growth. This is accompanied with a larger increase in inflation and interest rates.

Second, in Figure 10, we compare the response of bank lending to the sanctions

Figure 9: Local projections under high versus low credit growth

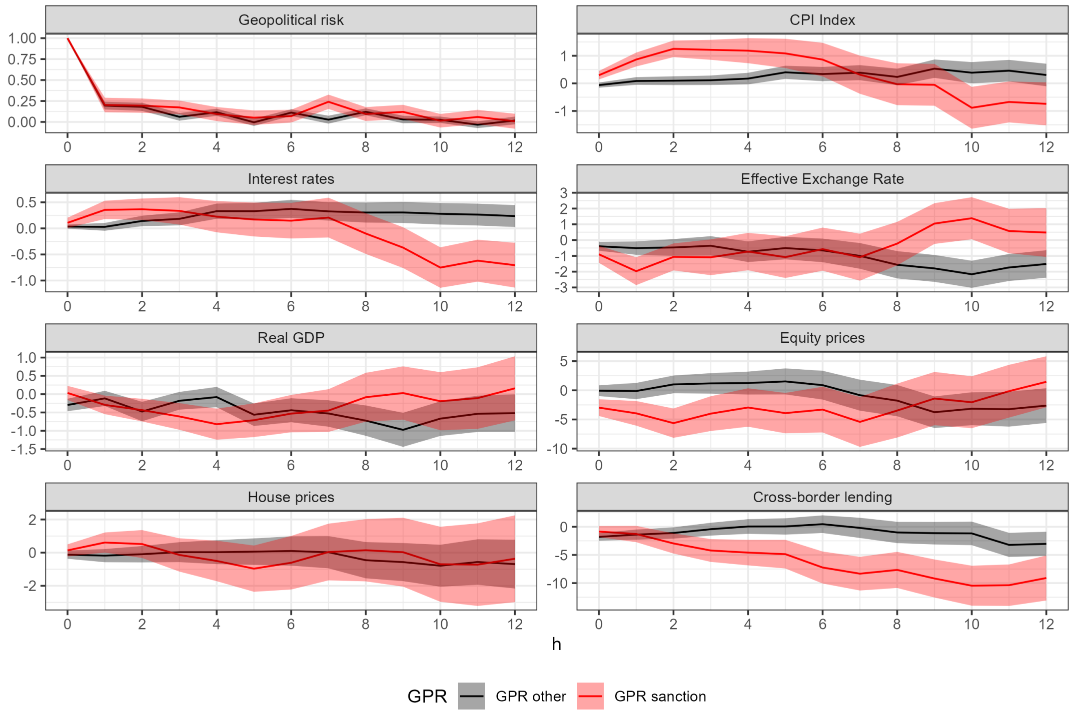


Notes: Shaded area and areas between dotted lines denote 68% confidence interval around mean estimates.

component of geopolitical risk versus the residual component. As per the results in Table 5, the sanctions component of geopolitical risk has a larger effect on bank lending. In addition, the sanctions component leads to a larger decline in real GDP and equity prices and a larger depreciation of the nominal effective exchange rate in the near-term. This also results in a sharper increase in the consumer price index, suggesting that sanctions manifest as a supply shock that disrupts targeted industries and institutions. One surprising phenomenon is around the two-year horizon, exchange rates appear to appreciate while central bank policy rates fall. That said, cross border lending continues to decline at this horizon, highlighting the persistent impact of geopolitical risk.

Finally, we consider whether sensitivity of cross-border lending depends on the currency in which loans are denominated. Figure 11 compares impulse responses of dominant currency lending (in US dollars) compared to non-dollar lending in general, and euro- and sterling-denominated loans (red lines and swathes) in particular. As

Figure 10: Local projections of sanctions risk



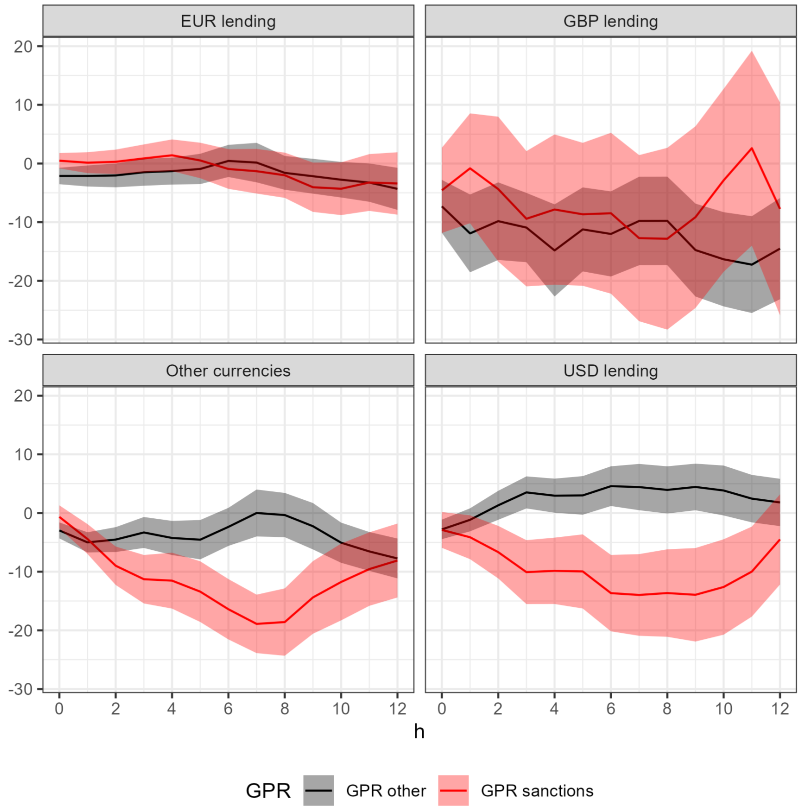
Notes: Shaded area and areas between dotted lines denote 68% confidence interval around mean estimates.

part of this, we distinguish between the sanctions and non-sanctions component of geopolitical risk.

This shows that dollar-denominated lending is particularly sensitive to the overlap of geopolitical and sanctions risk but unresponsive to the residual component of geopolitical risk. By contrast, loans in other currencies are sensitive to all components of geopolitical risk, while euro- and sterling-denominated lending appear also comparatively less sensitive to sanctions-related geopolitical risks.[13] This result may be driven by the experience of cross-border lending following sanctions imposed on Russia after 2014, after which the share of global cross-border lending to Russia denominated in US dollars declined from 65% to 25%, whereas the share of euro-denominated lending rose from 20% to 45% (Garofalo et al. (2025)).

[13] Sterling-denominated lending falls significantly following an increase in non-sanctions related geopolitical risk.

Figure 11: Local projections in different currencies



Notes: Shaded area and areas between dotted lines denote 68% confidence interval around mean estimates. Local projections are smoothed using a moving average, with a window size of two.

8 Conclusion

We examine the impact of geopolitical risk on cross-border bank lending. We combine data on cross-border lending by UK banks to individual borrowers based abroad from confidential large exposures supervisory reporting with a firm-specific measure of geopolitical risk based on firms earnings calls. Combining granular firm-level data points with tight fixed effect specifications allow us to estimate a causal effect of firm-level geopolitical risk on cross-border lending. We also use cross-border bank lending from the BIS to cross-check the results from the large exposures dataset and to examine possible transmission channels of geopolitical risk to lending.

We show that geopolitical risk has significant and heterogeneous effects on cross-border bank lending. Greater financial stability risks - indicated by higher credit or house price growth - is associated with a larger impact of geopolitical risk. The impact is also greater for less capitalised banks, and for tradable industries compared to non-tradable industries, with business cycle dynamics playing a key role in the transmission of geopolitical risk to lending. Finally, lending to energy and to defence-related sectors appears to increase in response to higher geopolitical risk, with banks potentially anticipating higher profitability in those sectors as risk increase.

Our results re-emphasise that geopolitical risks may have significant spillovers to macroeconomic and financial stability. The volume and composition of banks' cross-border lending is sensitive to geopolitical risk, while this effect may be amplified by overseas financial stability risks.

Further analysis may be helpful to substantiate the interaction between geopolitical alignment and cross-border lending. We would expect that geopolitical alignment or cultural similarity to have a significant impact on the response to geopolitical risk. This could be for political reasons (as conjectured by De Haas et al. (2025)) but there can be other reasons related to fundamentals. For example, increased geopolitical risk is likely to make it harder to screen and monitor loans, increases the probability of expropriation as well as making it harder to enforce loan contracts. We expect that these effects are likely to be lessened in bank from countries which are more aligned or similar.

In light of our results, it is crucial that macroeconomic policymakers monitor geopolitical risks, both domestically and abroad, and deepen understanding of how this transmits to macro-financial stability.

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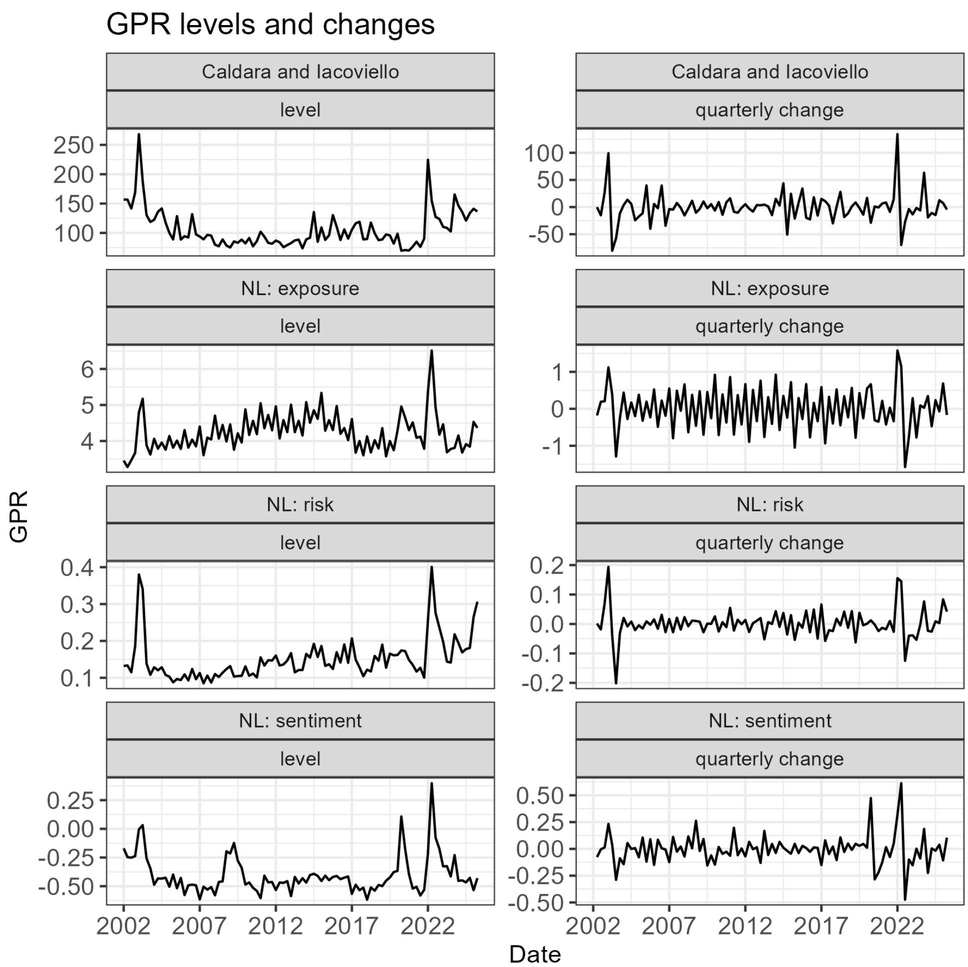
A Appendix: Geopolitical risk and its subcomponents

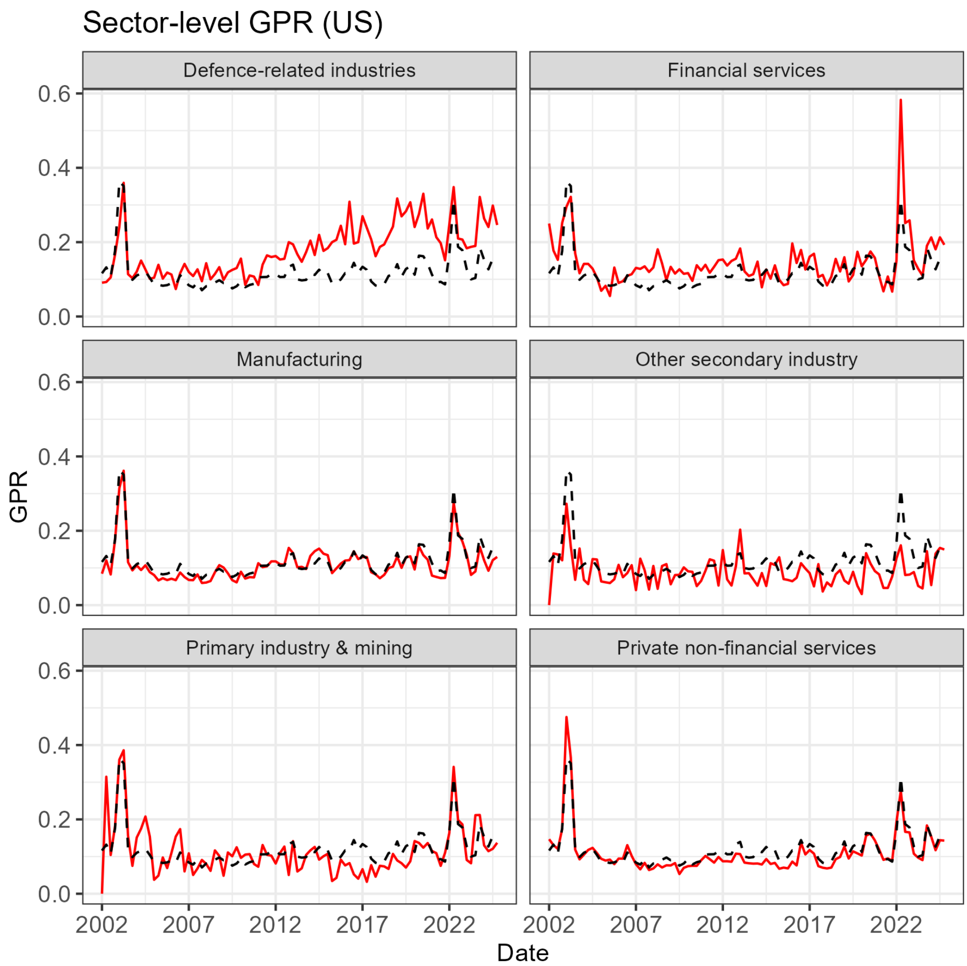
Augmented Dickey-Fuller tests reject the null that the global indices are not stationary. Visual inspection of the levels series in Figure A1 also suggest that the levels series mean-revert, even after major geopolitical events (such as Russia's invasion of Ukraine in 2022Q1). Autocorrelation functions also suggest that country-level risk metrics mean-revert. This suggests that using either quarterly changes or levels is appropriate for our analysis, depending on the broader regression specification we use.

Figure A1: geopolitical risk levels vs changes



Finally, Figure A2 illustrates time series variation across sectors in the United States, as per our preferred sector groupings. This shows that disaggregating to a higher dimension of granularity - in this case by sector as well as by country (shown in the red lines) - affords additional variation, over and above that of the country-level time series (dotted black lines). For instance, geopolitical risk in defence-related industries steadily increased from 2010 onwards, whereas risks were higher and more volatile for other secondary industries (including construction) in the 2000s. Most recently, financial services saw the largest spike in geopolitical risks after the start of the Russia-Ukraine war, after a swathe of sanctions targeting the financial sector were imposed.

Figure A2: geopolitical risk levels vs changes



Note: Observations for 2025 and public services omitted.

List of search terms for geopolitical risk[14]

war OR military OR terror* OR geopolitical OR conflict OR ″Middle East″ OR Iraq OR Afghanistan OR Iran OR Syria OR Libya OR Ukrain* OR Russia* OR ″North Korea″ OR Venezuela OR coup OR expropriation OR confiscation OR nationalism OR security OR protest* OR country OR countries OR political OR retaliation OR unrest OR geograph* OR troop* OR sanction OR sanctions OR embargo OR wars OR warfare OR army OR navy OR weapon* OR combat OR missile* OR immigration OR diplomacy

List of search terms for sanctions risk

″Middle East″ OR Iraq OR Afghanistan OR Iran OR Syria OR Libya OR Ukrain* OR Russia* OR ″North Korea″ OR Venezuela OR ″OFAC″ OR ″EU sanctions″ OR ″UN sanctions″ OR ″UK sanctions″ OR export restriction* OR export control* OR export ban* OR trade sanction* OR trade restriction* OR import restriction* OR import ban* OR import control* OR trade control* OR trade ban* OR asset freeze OR frozen asset* OR economic sanction* OR international sanction* OR travel ban* OR embarg*

[14] Asterisk denotes all words starting with a given set of letters.

B Appendix: Further tables and figures

Table B1: Sector classification

Group	NACE	Sector	SIC
Primary industry and mining	A	Agriculture, forestry and fishing	0100-0999
	B	Mining and quarrying	1000-1499
Manufacturing	C	Manufacturing	2000-3999
Other secondary industry	D	Electricity, gas, steam and air conditioning supply	4900-4940; 4956-4999
	E	Water supply; sewerage, waste management and remediation	4941-4955
	F	Construction	1500-1799
Financial services	K	Financial and insurance activities	6000-6499
Public services	O	Public administration and defence; compulsory social security	9000-9999
Private non-financial services	G	Wholesale and retail trade; repair of motor vehicles and motorcycles	5000-5999
	H	Transportation and storage	4000-4799; 7000-7099
	I	Accommodation and food service activities	7800-7899; 4800-4899
	J	Information and communication	4800-4899
	L	Real estate activities	6500-6799
	M	Professional, scientific and technical activities	0741-0742; 6800-6999; 7200-7299; 7600-7899; 8100-8199; 8300-8399; 8700-8799
	N	Administrative and support service activities	4700-4799; 7334; 7338; 7350-7599
	P	Education	8200-8299
	Q	Human health and social work activities	8000-8099
	R	Arts, entertainment and recreation	7336; 7900-7999; 8400-8699
	S	Other service activities	8900-8999
	U	Activities of extraterritorial organizations and bodies	9271

Table B2: Defence-related industries

Sector	SIC	NACE
Instruments and appliances for measuring testing and navigation	3812	**C**2651
Private security and systems service	7381-7382	**N**8010-**N**8020
Electronic components and boards	3671-3679	**C**2600-**C**2601
Computer programming and management	7371-7376	**J**6201-**J**6203
National security/Public defence	9711	**O**8422
Air and spacecraft and related machinery	3721-3724; 3760-3769	**C**3030
Military fighting vehicles	3261	**C**3040
Manufacture of weapons and ammunition	3482-3489	**C**2540
Other research and experimental development on natural sciences and engineering	8711; 8731	**M**7219

Table B3: Large exposures to different sector groups

	Gross exposure (£bn)	of which: matched (£bn)
Primary industry & mining	15.60	4.50
Manufacturing	174.10	102.60
Other secondary industry	67.20	18.20
Financial Services	1568.50	711.00
Public Services	692.40	0.00
Defence-related industries	12.70	7.90
Private non-financial services	218.60	42.70

Note: Data points from 2019Q4, excluding UK lending.

Table B4: Data sources for macroeconomic data

Jurisdiction	GDP	CPI	Policy rate	Exchange rate	Equities	House price	Credit
United Kingdom	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
United States	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Germany	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
France	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Hong Kong	Nat. source[a]	BIS	BIS	BIS	LSEG	BIS	BIS
Japan	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
China	Nat. source[b]	BIS	BIS	BIS	LSEG	BIS	BIS
Netherlands	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
South Korea	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Italy	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
India	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Switzerland	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Canada	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Norway	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Spain	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Mexico	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Belgium	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Australia	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Philippines	Nat. source[c]	BIS	BIS	BIS	LSEG	BIS	BIS
Brazil	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Austria	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Ireland	OECD	BIS	BIS	BIS	LSEG	BIS	BIS

(countinued overleaf)

[a]Census and Statistics Department, Hong Kong
[b]National Bureau of Statistics of China
[c]Philippine Statistics Authority

Jurisdiction	GDP	CPI	Policy rate	Exchange rate	Equities	House price	Credit
(countinued)							
Indonesia	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Thailand	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Denmark	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
South Africa	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Finland	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Malaysia	Nat. source[d]	BIS	BIS	BIS	LSEG	BIS	BIS
Sweden	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Russia	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Israel	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Czech Republic	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Portugal	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Chile	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Greece	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Poland	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
New Zealand	OECD	BIS	BIS	BIS	LSEG	BIS	BIS
Morocco	Nat. source[e]	BIS	BIS	BIS	LSEG	BIS	BIS

[d]Department of Statistics, Malaysia
[e]Haut-Commissariat au plan, Morocco

Table B5: Regression Results (country-level GPR)

	$dEXP_{b,c,t}$	$dEXP_{b,c,t}$	$dEXP_{b,c,s,t}$	$dEXP_{b,c,s,t}$	$dEXP_{b,c,s,t}$
	(1)	(2)	(3)	(4)	(5)
$dGPR_{c,t}$	-2.421	-1.587			
	(1.608)	(1.706)			
$dGPR_{c,t-1}$	-2.335	-1.098			
	(1.982)	(2.177)			
$dGPR_{c,t-2}$	-1.602	-0.542			
	(1.716)	(1.873)			
$dGPR_{c,t-3}$	-1.339	-0.871			
	(1.379)	(1.513)			
$dGPR_{c,s,t}$			-0.959	-0.910	-2.262**
			(0.848)	(0.923)	(1.115)
$dGPR_{c,s,t-1}$			-1.378	-0.991	-2.304*
			(0.981)	(1.101)	(1.302)
$dGPR_{c,s,t-2}$			-0.307	-0.322	-1.471
			(0.963)	(1.136)	(1.414)
$dGPR_{c,s,t-3}$			-0.346	0.105	-0.735
			(0.826)	(0.932)	(1.194)
Fixed effects	b,c,t	b-t,c	b,c,s,t	b-t,c-t,s-t	b-s-t,c-t
No. Observations	35994	31388	39495	33291	27018
Cum. GPR effect	-7.698	-4.097	-2.99	-2.119	-6.773
(p-value)	0.134	0.459	0.3	0.516	0.089
R^2	0.024	0.186	0.025	0.230	0.372
Adjusted R^2	0.015	0.059	0.018	0.079	0.075

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (1) adjusted to a bank-country (columns 1-2) or bank-country sector panel (columns 3-5). The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to country (c) (or also sector s) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the country-time level (columns 1-2) and country-sector-time level (columns 3-5).

Table B6: Sector heterogeneity (country-sector panel)

	$dEXP_{b,c,s,t}$	$dEXP_{b,c,s,t}$	$dEXP_{b,c,s,t}$	$dEXP_{b,c,s,t}$
	(1)	(2)	(3)	(4)
$dGPR_{c,s,t}$	-2.080*	-1.517	-2.300**	-2.397**
	(1.161)	(1.432)	(1.127)	(1.119)
$dGPR_{c,s,t-1}$	-1.943	-0.820	-2.265*	-2.386*
	(1.348)	(1.758)	(1.316)	(1.306)
$dGPR_{c,s,t-2}$	-0.956	-1.272	-1.582	-1.456
	(1.470)	(2.004)	(1.425)	(1.419)
$dGPR_{c,s,t-3}$	-0.473	0.738	-0.915	-0.715
	(1.237)	(1.577)	(1.209)	(1.198)
$dGPR_{c,s,t} * DUM_s$	-2.395	-1.756	4.179	28.830**
	(4.639)	(2.270)	(7.728)	(11.599)
$dGPR_{c,s,t-1} * DUM_s$	-4.636	-3.187	-3.632	10.067
	(4.828)	(2.600)	(8.620)	(14.550)
$dGPR_{c,s,t-2} * DUM_s$	-6.282	-0.213	10.121	-9.999
	(4.643)	(2.684)	(9.124)	(11.046)
$dGPR_{c,s,t-3} * DUM_s$	-2.599	-3.158	16.691**	-6.702
	(3.667)	(2.244)	(7.077)	(10.771)
Sector	Manufacturing	Fin. services	Defence	Energy
Fixed effects	b-s-t,c-t	b-s-t,c-t	b-s-t,c-t	b-s-t,c-t
No. Observations	27014	27014	27014	27014
Cum. GPR baseline	-5.452	-2.871	-7.062	-6.954
(p-value)	0.188	0.598	0.08	0.082
Cum. GPR interaction	-15.913	-8.314	27.359	22.197
(p-value)	0.231	0.275	0.219	0.558
Cum. GPR sector	-21.365	-11.185	20.297	15.243
(p-value)	0.094	0.047	0.354	0.686
R^2	0.372	0.372	0.372	0.372
Adjusted R^2	0.075	0.075	0.075	0.075

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (2) but in a country-sector panel. The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to sector (s) in country (c) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the country-sector-time level.

Table B7: Sensitivity analysis: regression specification

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR_{f,t}$	-0.595	-0.557	-0.928	-1.350**
	(0.771)	(0.411)	(0.596)	(0.589)
$dGPR_{f,t-1}$	-0.972	-1.006**	-1.417*	-1.263*
	(0.963)	(0.471)	(0.727)	(0.715)
$dGPR_{f,t-2}$	-0.650	-0.833*	-1.053	-0.989
	(0.962)	(0.459)	(0.748)	(0.742)
$dGPR_{f,t-3}$	-1.282*	-0.732*	-1.278**	-1.000*
	(0.769)	(0.383)	(0.602)	(0.582)
$dEXP_{b,f,t-1}$				-0.182***
				(0.015)
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f
Robustness	Net exposure	No. winzor	Inc. 2022Q2	Inc. LDV
No. Observations	23066	23454	24146	20096
Cum. GPR effect	-3.499	-3.128	-4.676	-4.602
(p-value)	0.197	0.020	0.025	0.028
R^2	0.360	0.389	0.388	0.419
Adjusted R^2	0.192	0.228	0.228	0.256

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (1). The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Table B8: Sensitivity analysis: other GPR metrics

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR^{exposure}_{f,t}$	-0.053		-0.151	
	(0.080)		(0.113)	
$dGPR^{exposure}_{f,t-1}$	-0.084		-0.141	
	(0.089)		(0.122)	
$dGPR^{exposure}_{f,t-2}$	-0.048		-0.174	
	(0.087)		(0.121)	
$dGPR^{exposure}_{f,t-3}$	-0.123		-0.111	
	(0.080)		(0.116)	
$dGPR^{sentiment}_{f,t}$		-0.021		-0.009
		(0.207)		(0.316)
$dGPR^{sentiment}_{f,t-1}$		0.054		-0.035
		(0.245)		(0.392)
$dGPR^{sentiment}_{f,t-2}$		-0.311		-0.414
		(0.247)		(0.393)
$dGPR^{sentiment}_{f,t-3}$		0.0002		-0.119
		(0.201)		(0.317)
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-t,f	b-t,c-t,f
Sample	All observations	All observations	Fin. services	Fin. services
No. Observations	23454	23454	13349	13349
Cum. GPR effect	-0.309	-0.278	-0.577	-0.578
(p-value)	0.217	0.695	0.093	0.620
R^2	0.389	0.389	0.436	0.436
Adjusted R^2	0.228	0.228	0.245	0.245

Note: *p<0.1; **p<0.05; ***p<0.01. This table reports the estimation results for equation (1). The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.

Table B9: Sensitivity analysis: including UK lending

	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$	$dEXP_{b,f,t}$
	(1)	(2)	(3)	(4)
$dGPR_{f,t}$	-0.985*	-0.977*	-0.934*	-0.793
	(0.597)	(0.565)	(0.566)	(0.545)
$dGPR_{f,t-1}$	-1.502**	-1.579**	-1.580**	-1.478**
	(0.726)	(0.703)	(0.694)	(0.678)
$dGPR_{f,t-2}$	-1.294*	-1.199*	-1.218*	-1.134*
	(0.752)	(0.712)	(0.710)	(0.683)
$dGPR_{f,t-3}$	-1.299**	-1.546***	-1.585***	-1.488***
	(0.595)	(0.568)	(0.557)	(0.549)
$dGPR_{f,t} * DUM_{b,c}$	1.270	2.042	2.754	0.920
	(1.474)	(1.354)	(1.764)	(2.066)
$dGPR_{f,t-1} * DUM_{b,c}$	0.237	0.843	1.507	-0.140
	(1.836)	(1.662)	(2.346)	(2.070)
$dGPR_{f,t-2} * DUM_{b,c}$	0.753	0.298	0.825	-0.464
	(1.744)	(1.752)	(2.294)	(2.512)
$dGPR_{f,t-3} * DUM_{b,c}$	-1.101	0.062	0.808	-1.064
	(1.391)	(1.406)	(1.793)	(2.029)
Fixed effects	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f	b-t,c-s-t,f
Interaction	uk_c	$home_{b,c}$	$uk_c^{*}home_{b,c}$	$(1 - uk_c)^{*}home_{b,c}$
No. Observations	28012	28012	28012	28012
Cum. GPR baseline	-5.079	-5.3	-5.316	-4.893
(p-value)	0.015	0.009	0.008	0.012
Cum. GPR interaction	1.159	3.246	5.894	-0.748
(p-value)	0.826	0.473	0.33	0.904
Cum. GPR overall	-3.92	-2.054	0.578	-5.641
(p-value)	0.417	0.634	0.921	0.36
R^2	0.374	0.374	0.374	0.374
Adjusted R^2	0.217	0.217	0.217	0.217

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. This table reports the estimation results for equation (2) replacing the sectoral interactions with a variable measuring whether flows are to the UK or to a bank's home jurisdiction. The dependent variable is the quarterly percentage change in gross bank exposures by bank (b) to firm (f) at time (t). The data are quarterly from 2015Q1 to 2024Q4. Standard errors are clustered a the firm-time level.