Violent Conflict and Cross-Border Lending

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Abstract

How do violent conflicts shape cross-border lending? Using data on syndicated loans by 14,021 creditors to firms in 179 countries (1989–2020), we document a dual effect: foreign banks reduce overall lending relative to domestic banks but significantly increase financing to military and dual-use sectors during conflicts. This reallocation is stronger among lenders less specialized in the conflict country, more specialized in military lending, and domiciled in politically non-aligned nations. Effects are geographically contained and temporally limited, dissipating post-conflict. Our findings reveal how global banks strategically redirect credit toward military sectors during armed conflicts, despite reducing overall country exposure.

JEL classification: D74, F34, F40, G15, G21

Keywords: Cross-border lending, syndicated loans, violent conflict, geopolitical risk, bank specialization

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1 Introduction

Although the world has enjoyed a relatively peaceful period since the carnage of World War II (Pinker, 2011), peace has been the exception rather than the rule throughout much of human history. Russia's war on Ukraine, escalating tensions in the Middle East, and protracted civil wars in Myanmar, Sudan and Yemen serve as sobering reminders of this reality and have thrust geopolitical conflict back to the fore.

While economists have thoroughly examined the direct and indirect economic consequences of war (Barro and Lee, 1994; Davis and Weinstein, 2002; Abadie and Gardeazabal, 2003; Acemoglu, Johnson and Robinson, 2005; Poast, 2005; Tooze, 2006; Glick and Taylor, 2010) and how states leverage sovereign debt to support their military endeavors (Kremer and Jayachandran, 2006; Reinhart and Rogoff, 2009; Zielinski, 2016), the relationship between private finance and armed conflict remains underexplored. We examine this relationship through the lens of cross-border lending during violent conflicts.

Two opposing hypotheses guide our empirical analysis. On the one hand, existing literature shows that cross-border lenders tend to "run for the exit" when faced with negative shocks to the local economy, such as systemic banking crises. This holds especially in the absence of strong relationships between creditors and borrowers (Giannetti and Laeven, 2012; De Haas and Van Horen, 2013). Historical and contemporary evidence also indicates that banks are typically wary of war's destabilizing economic effects (Kirshner, 2007), particularly when a conflict seriously damages corporate assets and diminishes firms' ability to pledge collateral (Shpak, Earle, Gehlbach and Panga, 2023). This literature thus suggests that cross-border lending should decline when countries experience violent conflict.

Conversely, armed conflict may generate countervailing forces that increase demand for cross-border credit, particularly in defense-related sectors. Foreign banks, less directly impacted by local hostilities, may be better positioned to accommodate this demand compared to domestic banks facing immediate conflict-related constraints (such as physical damage to banking infrastructure and liquidity pressures from deposit withdrawals). Cross-border lenders can then emerge as pivotal financiers of military production in conflict zones. Anecdotal evidence supports this idea. A notorious case involves the Italian Banca Nazionale del Lavoro, which used its US branch to grant \$3 billion in unauthorized credits to Iraq (1988-1989), with about \$600 million funding military technology (CIA, 1989). More broadly, estimates indicate that during 2020–2022 alone, financial institutions provided \$1 trillion to the global defense industry (Longo, Meggiolaro and Felipe, 2024), with Europe's 15 largest banks lending €88 billion to arms companies selling to conflict zones (Oudes, Slijper and Uiterwaal, 2022).

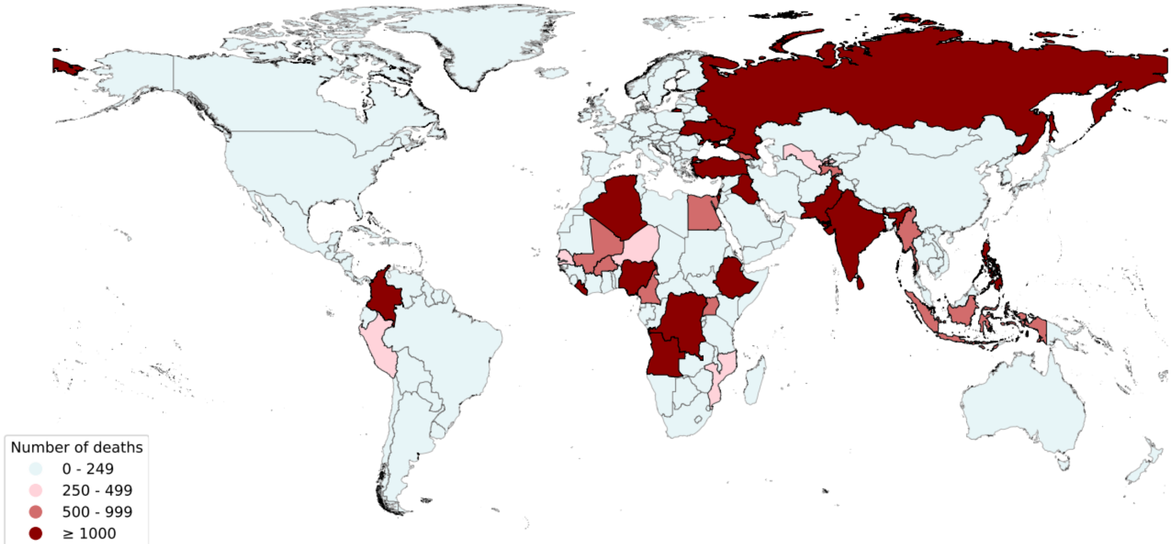
Our aim is to move beyond historical and anecdotal evidence by systematically analyzing how foreign credit flows respond to violent conflicts. To do so, we leverage comprehensive syndicated loan data from DealScan, covering 1.3 million loans by 14,021 lenders to 97,169 firms across 179 countries during 1989–2020. Cross-border credit is a key component of global capital flows, and almost three-quarters of all cross-border credit to both developed and emerging countries comes in the form of syndicated loans (Doerr and Schaz, 2021).

We merge this information with data from the Uppsala Conflict Data Program (UCDP), which provides detailed and complete information on armed conflicts, including battlefield death counts. In the three decades studied, civil wars and other intrastate hostilities comprise the majority of violent conflicts. Figure 1 shows that in our combined DealScan–UCDP dataset, 25 countries experienced at least one year with more than 500 battlefield deaths, and 16 countries saw at least one year exceeding 1,000 battlefield deaths.

Next, we systematically identify military-related borrowers by distinguishing primary military sectors (exclusively producing defense goods) and dual-use sectors (civilian goods with military applications). Drawing on the UK Strategic Export Control List, we map relevant keywords to 4-digit SIC codes and employ an AI-based approach to assess military relevance. We retain 10 primary military plus 79 dual-use sectors with at least 50% average military-use probability, together representing 17% of our syndicated lending sample.

Drawing on this new dataset, we start with an aggregate-level analysis that compares

Figure 1. Conflict Countries by Annual Battlefield Deaths



Note: This figure shows countries where annual battle-field related deaths exceeded 250, 500, or 1,000 at least once during 1989-2020 and where at least one firm received a syndicated loan during this period. The nature and timing of each conflict is described in Appendix Table A.I. Data sources: Uppsala Conflict Data Program and DealScan.

lending patterns by foreign versus domestic bank groups to military versus non-military sectors during conflicts. We establish two main results. First, foreign banks reduce overall lending to conflict countries relative to domestic banks—consistent with a "flight home" effect. Second, in crisis times, cross-border lenders *increase* their lending to military-related sectors. In short, we show that violent conflicts trigger both a contraction in overall credit provision and a reallocation of cross-border lending from non-military to defense-related sectors. This dual pattern also emerges clearly in event studies around the onset of conflict.

Next, we conduct a loan-level analysis to examine individual bank-firm lending decisions during conflicts. Using comprehensive fixed effects, we confirm the aggregate patterns: foreign banks reduce lending to non-military firms by 27% during conflicts relative to domestic banks, while simultaneously increasing military sector lending by 24% more than domestic banks. These baseline findings prove robust to varying conflict intensity thresholds, alternative sector classifications, different econometric specifications, alternative treatments of missing data, and restrictions to specific country or lender subsamples.

We then turn to supply and demand decomposition tests to isolate the underlying mechanisms. By saturating our specifications with either bank-year or country-sector-year fixed effects, we separate supply and demand forces. The results reveal that the military lending increase stems primarily from heightened demand by defense firms that foreign banks are better positioned to meet, rather than proactive supply-side targeting by lenders. Meanwhile, the broader reduction in foreign bank exposure to conflict countries persists even after controlling for demand factors, consistent with a classic supply-driven "flight home" effect.

In a next step, we analyze whether banks align lending practices with their home country's geopolitical interests during conflicts. We classify countries using formal geopolitical blocs (BRICS vs. NATO/G7) and UN General Assembly voting patterns to distinguish Western, Eastern, and neutral alignments. While banks from all orientations increase military lending during conflicts, the destination patterns reveal strategic considerations: banks preferentially direct military financing toward non-aligned or politically distant countries while avoiding geopolitically similar nations. Western banks, for instance, significantly increase military lending to Eastern and neutral conflict countries but reduce it to Western conflict zones. This suggests that profit motives dominate when lending to "out-group" countries, while political constraints or regulatory scrutiny limit military financing within geopolitical blocs.

To further examine mechanisms, we analyze how bank specialization shapes cross-border lending during violent conflicts, using measures of relative specialization (Paravisini, Rappoport and Schnabl, 2023). The results reveal a generalized flight-home effect, with all banks reducing non-military lending to conflict zones. However, this broad retreat is systematically offset by increased military lending from two distinct bank types: banks without prior country specialization aggressively redirect capital toward military sectors in unfamiliar conflict zones, while banks with established military sector expertise also sharply increase defense lending during conflicts. This indicates that our documented reallocation is specifically driven by cross-border lenders with military expertise but limited country-specific relationships. Such banks appear relatively well positioned to capitalize on conflict-induced credit demand without having to compromise established country-specific client relationships.

Several extensions help to delineate the scope and boundaries of our main results. We find no evidence of spillover effects to neighboring non-conflict countries, indicating that foreign banks target primary conflict countries rather than broader regions. Moreover, the relative increase in military lending dissipates completely within three years post-conflict, suggesting banks react to immediate conflict dynamics rather than long-term strategic (re-)positioning. Finally, both state-owned and private banks, as well as bank and non-bank lenders, display similar reallocation patterns, indicating that political ownership does not drive our results.

Related literature. This paper contributes to three strands of the literature. First, we extend research on international private capital flows. Previous work has analyzed how investors allocate capital abroad (Lane and Milesi-Ferretti, 2007; Coeurdacier and Rey, 2013; Bruno and Shin, 2015; Maggiori, Neiman and Schreger, 2020; Coppola, Maggiori, Neiman and Schreger, 2021), how this allocation affects recipient economies (Calvo, Leiderman and Reinhart, 1993), and how private capital flows co-move as part of a global cycle (Rey, 2015). Several papers examine how cross-border credit flows, especially in the form of syndicated lending, can transmit financial and real-economic shocks across borders.[1] Our analysis extends this literature by revealing a contrasting lending dynamic during violent conflicts: while cross-border lenders significantly reduce overall lending, they simultaneously redirect capital toward sectors positioned to benefit from local instability, particularly the military-industrial complex. This pattern confirms existing evidence about distance constraints on cross-border lending, while revealing a new mechanism through which foreign banks reallocate credit toward military sectors during armed conflicts.

Second, we contribute to an emerging literature that examines how financial markets interact with military conflict. Previous research has primarily focused on sovereign bor-

[1] E.g., Cetorelli and Goldberg (2011); Giannetti and Laeven (2012); Popov and Udell (2012); De Haas and Van Horen (2013); Cerutti, Hale and Minoiu (2015); Hale, Kapan and Minoiu (2020); Doerr and Schaz (2021).

rowing. Horn, Reinhart and Trebesch (2024) document how wars trigger dramatic financial changes as government-to-government lending increases while overall private capital flows shrink. DiGiuseppe (2015) find that sovereign credit enables states to simultaneously finance military and civilian spending, circumventing budgetary constraints, while Federle, Rohner and Schularick (2025) demonstrate how financial access can drive military success: countries experiencing commodity windfalls significantly improve their chances of victory as they can ramp up military expenditures. Our contribution is to document how private cross-border credit flows can be a channel for military financing during violent conflicts, when domestic credit markets are often constrained (Mamonov, Ongena and Pestova, 2024).

Third, we shed light on the financial repercussions of geopolitical fragmentation. Recent papers document how global trade, investment, and supply chains have fragmented along geopolitical lines since the onset of Russia's invasion of Ukraine and escalating US-China trade tensions. These studies reveal a progressive fragmentation of economic linkages between rival geopolitical blocs, partially mitigated by emerging "connector" countries.[2]

An emerging literature has begun to explore how geopolitical tensions affect financial markets. Niepmann and Shen (2025) show that internationally active US banks respond to geopolitical risk by reducing cross-border and domestic lending, while maintaining credit supply through local affiliates in risky countries, a dynamic that generates significant economic spillovers. Danisewicz, Park, Schaeck and Zheng (2025) find that cross-border lenders strategically responded to Russia's counter-sanctions on the EU's agricultural sector by increasing lending and offering more favorable loan terms to this sector. They also show that banks with sector-specific expertise can mitigate economic disruptions in sanctioned industries. Efing, Goldbach and Nitsch (2023) find that while German banks reduced cross-border lending to sanctioned countries, their foreign affiliates in less regulated jurisdictions expanded credit. Similarly, Besedeš, Goldbach and Nitsch (2017), also for Germany, show that direct

[2] See Alfaro and Chor (2023); Chupilkin, Javorcik and Plekhanov (2023); Aiyar, Malacrino and Presbitero (2024); Chupilkin, Javorcik, Peeva and Plekhanov (2024); Gopinath, Gourinchas, Presbitero and Topalova (2025).

financial transactions with sanctioned countries decline but are partially replaced by flows through intermediary nations. Thus, both studies demonstrate how regulatory gaps allow private capital flows to adapt to and partially circumvent geopolitical restrictions.

Unlike this existing work on sanctions and regulatory arbitrage, we examine violent conflicts as a distinct shock that triggers asymmetric credit reallocation: foreign banks reduce civilian lending while simultaneously increasing military-sector financing, particularly in politically non-aligned countries. Our results complement Kempf, Luo, Schäfer and Tsoutsoura (2023), who find that ideological alignment shapes cross-border capital allocation during peacetime. By analyzing differential lending patterns from politically aligned versus non-aligned countries to conflict zones, we identify a previously unexamined channel through which geopolitical distance enables rather than constrains financial flows—specifically toward military sectors during armed conflicts.

2 Data

2.1 Data sources

Our analysis requires us to merge the data from the Uppsala Conflict Data Program (UCDP) with the Loan Pricing Corporation's (LPC) DealScan data. The UCDP provides comprehensive and harmonized information on armed conflicts and organized violence over nearly four decades. We focus on state-based armed conflicts, which cause most battle-related fatalities (Melander, Pettersson and Themnér, 2016). These are conflicts between two parties, of which at least one is a state government, resulting in at least 25 fatalities within a year. We aggregate battle deaths at the country-year level.

From DealScan, we collect comprehensive data on syndicated lending to corporations globally over a 31-year period (1989-2020). This extensive data set allows us to observe the universe of syndicated loan transactions, capturing lending relationships between financial institutions and borrowers across different countries, sectors, and time periods. We split each loan into syndicate member shares to create our unit of observation: a syndicated loan portion by an individual bank to an individual borrower in a given year. Since DealScan provides loan share distributions for only 26% of loans, we impute missing shares using each bank's historical average share from loans with known allocations and then re-weigh these shares so that they add up to 100%.[3] We convert amounts to US dollars and date each observation to the loan's origination year. DealScan provides the countries of both lenders and borrowers (we manually double check bank headquarters locations). In line with the literature (Mian, 2006; Giannetti and Laeven, 2012), we classify a loan as foreign when the bank or its parent company is incorporated in a different country than the borrower. For example, a loan to a Nigerian company from Citibank is considered foreign regardless of whether it comes from Citibank US or a local Citibank affiliate in Nigeria.

2.2 Identifying military and dual-use sectors

We categorize military-related sectors into two types: primary military and dual-use. Primary military sectors exclusively produce goods and technologies for military and defense purposes, such as missiles and tanks. In contrast, dual-use sectors produce goods, technologies, or services intended for civilian use but with a clear capability to perform military functions. For example, commercial aircraft engine technology can be readily adapted for fighter jets, with the same advanced materials, propulsion systems, and engineering principles serving both civilian transportation and military aviation needs.

Because the export of dual-use products can pose national security concerns, many countries create lists of items that require export authorization. We use the UK's Strategic Export Control List from the Department for Business and Trade (specifically the "*Military List*" and "*Dual-Use List*") to identify military and dual-use industries. From the first list, we collect key terms such as 'weapon', 'gun', 'artillery', 'tank', 'bomb', 'torpedo', 'missile' and 'explosives'. We then identify all 4-digit SIC codes on the NAICS/SIC website that

[3]Our results are robust to alternative imputation methods, such as splitting the overall loan equally across all banks in the syndicate (De Haas and Van Horen, 2013). See Appendix Table L.I.

mention these goods. This yields 10 primary military SIC codes.

For the dual-use list, we apply a similar but slightly adjusted approach. We extract keywords from the UK's dual-use category titles (such as 'nuclear' and 'aircraft') and search for these terms on the NAICS/SIC website. This generates 115 potential dual-use SIC codes. We then evaluate each sector's likelihood of military association by asking ChatGPT-4o to assess the probability of military production involvement for all 125 codes (10 primary military plus 115 dual-use sectors). We perform 50 iterations, randomly reordering the 125 SIC codes each time, and calculate the average probability for each sector (Appendix B describes this approach in more detail). The Spearman rank correlation in Figure B.I demonstrates very high consistency across iterations. Notably, ChatGPT-4o consistently assigns 95-100% probability to the 10 primary military sectors. We ultimately retain these 10 sectors plus 79 dual use sectors that have an average military-use probability of at least 50%. Across our sample, these 89 sectors account for 17% of total syndicated lending volume.[4]

An example of a syndicated loan in our data set that was disbursed to a firm in a dual use sector during a violent conflict is the 2014 facility by Bank of America, Merrill Lynch, ING, and UBS to Israel's Delek Group. Although this conglomerate has diversified interests, primarily in the energy sector, several of its activities have intersected with military and defense sectors, including providing fuel supply to military entities and operating fuel and service stations in occupied territories. Another example would be the 2015 syndicated loan arranged by a consortium of 15 African, American, Chinese, and European banks to INT Towers in Nigeria, a company specializing in telecommunications infrastructure. After receiving this syndicated loan, INT's parent company—IHS Towers Nigeria—donated an Information Communication Technology Center to the 6$^{\text{th}}$ Division of the Nigerian Army.

[4]Panel A (B) of Appendix Table D.I lists the 10 (79) SIC codes of the primary (dual use) military sectors. Each code links to at least one of the predefined categories of the UK dual use list in Annex I. See https://www.gov.uk/government/publications/uk-strategic-export-control-lists-the-consolidated-list-of-strategic-military-and-dual-use-items-that-require-export-authorization.

2.3 Descriptive statistics

Our starting sample spans the period 1989–2020 and contains 1,322,944 observations at the bank-firm-year level, reflecting 861,437 distinct bank-firm relationships, 14,021 unique creditors, and 97,169 unique borrowers.[5] Appendix Table C.I contains variable definitions while Appendix Table C.II presents summary statistics for all variables used in our analysis.

Our dependent variable, the logarithm of the loan amount at the bank-firm-year level, has a mean of 16.48 or $46.2 million. Foreign (cross-border) loans, in which banks lend money to firms in a different country, comprise 46% of all loans. Loans to dual-use military-related sectors represent 16.8% of our sample, while another 0.3% are for primary military applications. In terms of broader sector classifications, the services sector and the industry and manufacturing sector represent the largest shares at 34% and 24% of total loan recipients, respectively. The wholesale trade sector represents the smallest share, 6% of all loans. The mean distance between bank and firm headquarters is 3,810 km.

Regarding conflict exposure, 2% of the loans (30,252 loans) are extended to firms in countries experiencing a conflict with more than 500 battlefield deaths, while 1% (14,344) go to firms in countries with conflicts exceeding 1,000 battlefield deaths. Appendix Figure E.I displays the leading source countries of syndicated loans to military and dual-use sectors in conflict zones. Although the United Kingdom, United States, and Germany top this ranking, it also includes countries such as Singapore, the United Arab Emirates, and China.

3 Empirical strategy

3.1 Aggregate-level analysis

We first explore aggregate cross-border lending to military-related sectors during violent conflicts. Our goal is twofold: to explore whether these effects are economically significant

[5] In the analysis, we drop banks that provide only one loan, which removes roughly 7,000 unique creditors from the initial number of about 21,000 banks.

at the level of the aggregate economy and to understand how they compare to those stemming from domestic bank lending. We aggregate all bank-firm-year observations to the bank group-sector-country-year level, where 'bank group' refers to either all foreign or all domestic banks, and 'sector' to all borrowing firms operating in either military- or non-military-related sectors of an economy. We include zeros for country-year pairs without lending activity, creating a balanced panel that captures both intensive and extensive margins of cross-border lending during conflicts. We specify the following regression equation:

$$
\begin{aligned}
Loan_{gsct} = {} & \beta_0 \cdot Foreign_{gc} \\
& + \beta_1 \cdot Foreign_{gc} \times Conflict_{ct} \\
& + \beta_2 \cdot Foreign_{gc} \times Military_s \\
& + \beta_3 \cdot Foreign_{gc} \times Conflict_{ct} \times Military_s \\
& + \alpha_{rt} + \gamma_{vs} + \delta_{gs} + \chi_{st} + \phi_{gt} + \theta_{gc} + \varepsilon_{gsct}
\end{aligned}
\tag{1}
$$

where $Loan_{gsct}$ is the total loan amount (in billion US dollars) by bank group g to sector s in country c and year t, which is either zero (no syndicated loan) or strictly positive (at least one syndicated loan). As our data aggregation produces many zeros in the dependent variable, we employ the Poisson Pseudo Maximum Likelihood (PPML) estimator by Correia, Guimaraes and Zylkin (2020). $Conflict_{ct}$ is a dummy variable equal to one if the country experiences a violent conflict in year t. By construction, β_1 captures changes in aggregate credit by foreign banks to non-military firms in countries that encounter violent conflicts, relative to domestic banks, while β_2 reflects the differential lending by foreign banks to military sectors, relative to domestic banks, regardless of conflict status. β_3, our main coefficient of interest, captures changes in lending to the military sector by foreign lenders in response to violent conflict, relative to domestic banks.

The specification also includes the following high-dimensional fixed effects. First, α_{rt} are host region $\times$ year fixed effects that net out all time-varying aggregate shocks common to all destination countries within a region.[6] Second, γ_{vs} are violent conflict $\times$ sector fixed effects that absorb general changes in the expansion of the military versus non-military sectors during conflicts. Third, δ_{gs} are bank group $\times$ sector fixed effects that remove time-invariant differences between foreign and domestic creditors in their propensity to lend to military versus non-military sectors. Fourth, χ_{st} are sector $\times$ year fixed effects that account for changes in the relative importance of military versus non-military sectors over time, regardless of which bank group is lending. Fifth, ϕ_{gt} are bank group $\times$ year fixed effects that capture overall trends in syndicated lending by foreign versus domestic banks over time, across all sectors and countries, regardless of whether the latter encounter violent conflicts or not. Sixth, θ_{gc} are bank group $\times$ host country fixed effects that flexibly capture potential specialization of foreign banks in lending to particular destination countries. Because the data are aggregated over lender types and firms, we cannot hold constant background forces at the level of individual borrowers and creditors, as well as the home countries of foreign banks. We therefore view this specification as suggestive, though useful, to gauge whether any effects are meaningful in the aggregate.

Consistent with the earlier discussion, two hypotheses emerge. First, previous evidence suggests that cross-border lenders reduce credit to the corporate sector more than domestic banks in response to negative economic shocks (Giannetti and Laeven, 2012; De Haas and Van Horen, 2013). In this scenario, a violent conflict should lead cross-border lenders to "run for the exit" more than domestic lenders, in which case we expect $\beta_1 < 0$. In contrast, armed conflict can increase credit demand in military sectors, which domestic banks can struggle to meet, causing cross-border lenders to step in. Thus, cross-border lending to military-related sectors in conflict zones could increase, in which case we expect $\beta_3 > 0$.

[6] We consider the following regions: *ECA* is Europe and Central Asia, *EAP* is East Asia and Pacific; *Americas* are North America, Latin America, and the Caribbean; *MENA* is Middle East and North Africa; *SAR* is the South Asia region; and *SSA* is Sub-Saharan Africa.

3.2 Loan-level analysis

At the bank-firm-year level, we are interested in whether cross-border lenders engage in a reallocation of lending across firms in different sectors during times of violent conflict in a particular destination country. To that end, we specify the following regression equation:

$$\begin{aligned} Loan_{bfsct} = {} & \beta_0 \cdot Foreign_{bf} \\ & + \beta_1 \cdot Foreign_{bf} \times Conflict_{ct} \\ & + \beta_2 \cdot Foreign_{bf} \times Military_s \\ & + \beta_3 \cdot Foreign_{bf} \times Conflict_{ct} \times Military_s \\ & + \alpha_b + \theta_f + \mu_{ht} + \nu_{ct} + \delta_{vs} + \chi_{gs} + \phi_{gt} + \tau_{st} + \varepsilon_{bfsct} \end{aligned} \tag{2}$$

where $Loan_{bfsct}$ denotes total loans by bank b to firm f in sector s in country c (the borrowing firm's country of incorporation) in year t. As before, $Conflict_{ct}$ is a dummy equal to one if the country experienced a violent conflict in year t. $Military$ is a dummy equal to one if firm f's primary, secondary, or tertiary SIC code is part of the sector list in Table D.I.

In this specification, β_1 captures changes in cross-border credit to a firm in a non-military sector in a country experiencing violent conflict, relative to domestic lending. β_2 reflects the differential lending by foreign banks to military sectors relative to domestic banks, regardless of conflict status. β_3 captures how much the same cross-border lender changes lending to a firm in the military sector in response to violent conflict, relative to domestic banks.

Equation (2) is fully saturated with a battery of base and interactive fixed effects. Bank fixed effects α_b control for time-invariant differences in risk appetite, capital constraints, and lending policies across creditors that may have an independent effect on sectoral credit allocation. Firm fixed effects θ_f absorb time-invariant differences in credit demand or creditworthiness across firms, which may not be related to the military conflict. Both these fixed effects are crucial because variations in loan volumes could otherwise simply reflect persistent differences between banks and firms, rather than meaningful changes over time.

Next, we include bank incorporation ('home') country h × year t fixed effects (μ_{ht}) and firm incorporation (host) country × year t fixed effects (ν_{ct}). These absorb shocks common to all banks or firms, respectively, in their country of incorporation.

Finally, we include four sectoral interactive fixed effects. First, violent conflict v × sector s fixed effects (δ_{vs}) absorb sectoral lending differences during conflicts that are common to domestic and cross-border lenders. Second, bank group g × sector s fixed effects (χ_{gs}) capture time-invariant differences in the propensity to lend to the military sector by the group of foreign versus domestic lenders. Third, bank group g × year t fixed effects (ϕ_{gt}) netting out global trends in the propensity to extend loans abroad. Fourth, sector s × year t fixed effects (τ_{st}) account for time-varying aggregate shocks to the military sector that are common to both foreign and domestic lender groups. The variables $Conflict$, $Military$, $Foreign$, and $Conflict \times Military$ are not included on their own because they are absorbed by the corresponding fixed effects.

Our prior hypotheses extend to the disaggregated analysis. In line with the existing literature on cross-border versus domestic lending during crises, cross-border lenders may reduce their credit exposure to firms more strongly in response to local demand shocks, in which case we expect $\beta_1 < 0$. Alternatively, violent conflict could increase demand for military products, raising military firms' credit demand. Foreign banks, with a greater spare capacity and access to deeper internal capital markets, may be better positioned to increase lending to these firms, in which case $\beta_3 > 0$.

4 Baseline results

This section presents our empirical results at the aggregate level (Section 4.1) and loan level (Section 4.2). Section 4.3 discusses several robustness tests, after which Sections 4.5 and 4.6 investigate the role of geopolitical (mis)alignment and of bank specialization, respectively.

4.1 Aggregate results

Table 1 presents results from estimating different versions of Equation (1), using a balanced panel data set containing 179 countries, 32 years, information on whether lending stems from a foreign or domestic bank group, and on whether it is directed to firms in military or non-military sectors. This panel structure yields an initial sample of 22,912 observations at the country $\times$ year $\times$ bank group $\times$ sector level. The number of observations drops slightly to 22,652 in columns (1) to (3), and further to 20,354 in column (4), as the inclusion of additional high-dimensional fixed effects leads the PPML estimator to drop 'separated' observations (Correia et al., 2020).

In column (1), we include the variable $Foreign$ and its interaction with $Conflict$, controlling for host region $\times$ year fixed effects, as well as the level $Conflict$ effect. The evidence suggests that foreign lending typically exceeds domestic lending during non-conflict times, underscoring the importance of the cross-border segment of the syndicated loans market. At the same time, foreign and domestic lending adjust in a similar fashion when a country experiences a violent conflict. In column (2), we add the interaction of $Foreign$ and $Military$, as well as the triple interaction of $Foreign$, $Conflict$, and $Military$. In this regression, we document on average significantly less lending by foreign banks to the military sector, compared with domestic banks. Importantly, the positive and highly significant point estimate of β_3 reveals that this reverses during conflicts: compared to domestic banks, cross-border lenders *expand* their lending for defense-related projects.

This contrasting pattern is confirmed in column (3), where we add interactions of $Foreign$ $\times$ $Military$ fixed effects, $Military$ $\times$ year fixed effects, and $Foreign$ $\times$ year fixed effects. The latter two absorb the independent effect of sector and foreign (potentially nonlinear) aggregate trends. The estimated coefficient β_3 continues to be positive and significant at the 1% statistical level. Notably, the inclusion of the three high-dimensional fixed effects has almost no effect on the estimated magnitude of the β_3 coefficient.

Finally, in column (4) we add $Foreign$ $\times$ Host country fixed effects, which net out time-

Table 1. Cross-Border Lending to Military Firms During Violent Conflicts: Aggregate-Level Analysis

		Dependent variable: $Loan_{gsct}$			
		(1)	(2)	(3)	(4)
Foreign	β_0	0.532***	0.578***		
		(0.044)	(0.040)		
Foreign × Conflict	β_1	0.427	0.237	0.217	-0.606**
		(0.356)	(0.365)	(0.365)	(0.303)
Foreign × Military	β_2		-0.184***		
			(0.046)		
Foreign × Conflict × Military	β_3		1.679***	1.678***	1.647***
			(0.389)	(0.390)	(0.375)
Conflict		✓	✓	✓	✓
Host Region × Year FE		✓	✓	✓	✓
Conflict × Military FE			✓	✓	✓
Foreign × Military FE				✓	✓
Military × Year FE				✓	✓
Foreign × Year FE				✓	✓
Foreign × Host Country					✓
N obs		22,652	22,652	22,652	20,354
N of host region × year clusters		229	229	229	229
R^2 (adj.)		0.433	0.480	0.483	0.856
Linear test: $\beta_1 + \beta_3 = 0$			*1.915****	*1.895****	*1.041****
			(0.212)	*(0.211)*	*(0.234)*

Note: This table shows the results from estimating Equation (1) using the Poisson Pseudo-Maximum Likelihood approach with high-dimensional fixed effects (Correia et al., 2020). The dependent variable is the absolute amount of total loans $Loan_{gsct}$ (in billions of US dollars) by bank group g to sector s in country c and year t. The dependent variable is winsorized at the 99.5th percentile. $Foreign_{gc}$ is a dummy equal to one (zero) when indicating aggregate cross-border (domestic) lending to country c. *Conflict* is a dummy variable equal to one if the country in which the firm is domiciled, experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). *Host Region* is either East Asia and Pacific; North America, Latin America, and the Caribbean; Middle East and North Africa; South Asia; or Sub-Saharan Africa. All regressions include fixed effects as specified. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the host region × year level and reported in parentheses.

invariant differences in lending to a particular country across domestic and foreign lenders. The point estimate of β_1 now turns negative and significant at the 5% statistical level. The negative β_1 implies that relative to non-conflict times, foreign banks significantly reduce non-military lending to countries experiencing a conflict. Importantly, we still obtain a positive and highly significant point estimate of β_3, which confirms that this general pattern does not hold for lending to military-related sectors. Compared to domestic banks, cross-border lenders in fact expand their lending for defense-related projects.

Numerically, the point estimates imply that relative to non-conflict times, lending by foreign banks to the non-military sector falls by $e^{-0.606} - 1$ during conflicts, or by 45.4 percent more than lending by domestic banks.[7] In contrast, lending by foreign banks to the military sector increases substantially by around $e^{-0.606+1.647} - 1$ during conflict times, or by around 183.2 percent more than lending by domestic banks (significant at the 1% level).

Figure 2 plots the annual coefficients for β_1 (panel *a*) and β_3 (panel *b*) over an event window spanning three years before and after the onset of conflict. The patterns in the figure provide visual support for the identification strategy and the regression results reported in Table 1. First, foreign lending to non-military firms declines sharply in the three years following the outbreak of conflict, relative to domestic lending. Second, this decline is mirrored by an immediate and sustained increase in foreign lending to military firms over the same period. Third, neither pattern is present in the pre-conflict years, suggesting that the results are not driven by pre-trends.

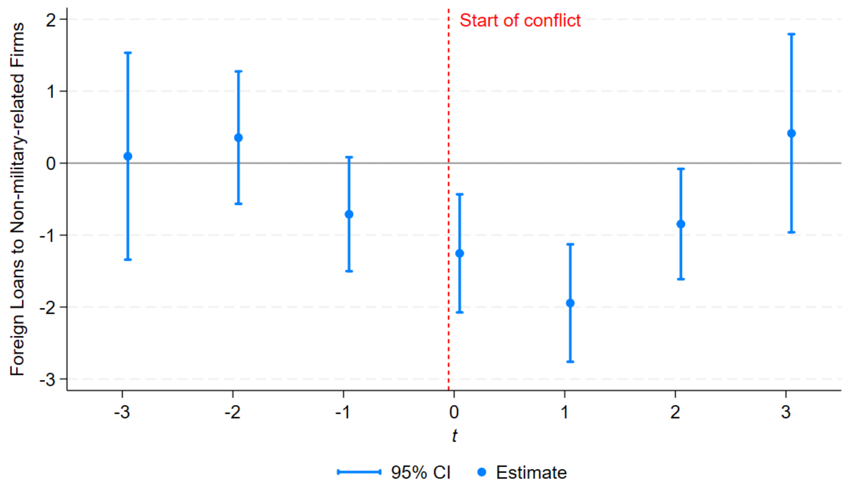
Robustness. We first examine the robustness of these findings to varying the classification of dual-use sectors. Specifically, we increase the AI-estimated probability threshold for military use from 50% to 90% in increments of 10 percentage points and check how the estimate of β_3 responds. Figure F.I in Appendix F illustrates that this estimate remains robust across thresholds and increases at the strictest thresholds (80% and 90%)—where both the number of military sectors and their share of syndicated lending are nevertheless smaller.

Second, we check the robustness of our inference to different clustering approaches. Figure G.I in Appendix G compares the baseline approach—clustering at the level of the eight host-

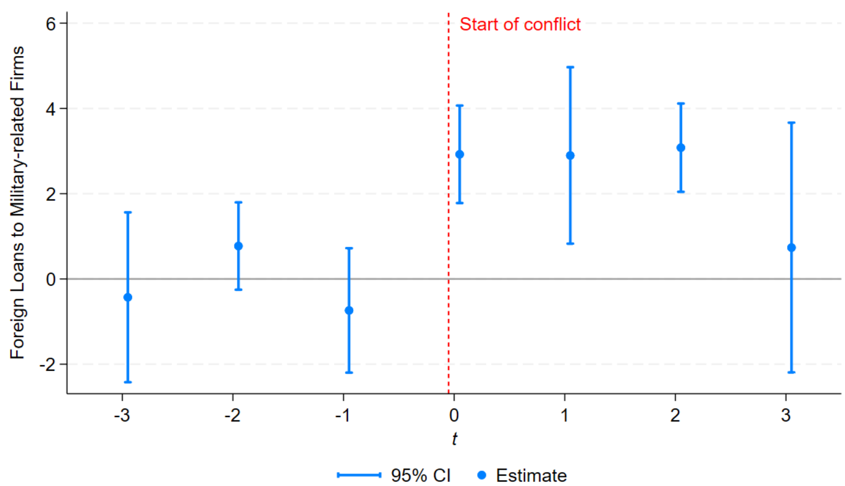
[7] Although the dependent variable is specified in levels (the absolute amount of loans), the PPML estimator models the conditional mean of the outcome as an exponential function of the regressors. As a result, coefficient estimates can be interpreted in percentage terms, similar to a log-linear model, even though the dependent variable is not log-transformed.

Figure 2. Cross-Border Lending Before and During Violent Conflicts: Event-Study Analysis at the Aggregate Level

(a) β_1: Foreign Lending to Non-Military Sectors



(b) β_3: Foreign Lending to Military Sectors



Note: The figure reports the regressions coefficients of β_1 and β_3 from the version of Equation (1) reported in Table 1, column (4), where the variable $Conflict$ has been replaced with year dummies for the period between three years before and three years after the conflict. The data is sourced from the Uppsala Conflict Data Program and DealScan.

country regions $\times$ 32 (256 clusters)—to six alternatives: (i) host-country clusters; (ii) host-country $\times$ year clusters; (iii) host-country $\times$ sector $\times$ year clusters; (iv) host region $\times$ sector

$\times$ year clusters; (v) host region $\times$ sector $\times$ conflict $\times$ year clusters; and (vi) host region $\times$ sector $\times$ conflict clusters. As Figure G.I indicates, our β_3 estimate remains statistically significant at the 1% level in each case.

Third, we apply the inverse hyperbolic sine (IHS) transformation to the dependent variable y (the absolute amount of loans), defined as $\ln(y + \sqrt{y^2 + 1})$. This transformation behaves similarly to the natural logarithm for large values but is well-defined at zero, making it more robust to extreme values in the right tail of the loan distribution. As shown in Appendix Table H.I, the results remain qualitatively unchanged, confirming the robustness of our baseline findings.

Finally, we estimate a specification in which the dependent variable is the share of military-related loans extended by bank group g in country c and year t, relative to total lending in that country and year. This addresses the potential concern that if a bank decides not to lend to a non-military firm and lend to a military firm instead—as opposed to simply lend to a military firm—our regression framework may misrepresent the extent of portfolio reallocation. The key explanatory variable becomes $Foreign \times Conflict$, which captures whether foreign banks increase their military lending share during conflicts relative to domestic banks. As shown in Table I.I, we continue to find a positive and significant coefficient on $Foreign \times Conflict$, indicating that cross-border lenders increase the share of their lending allocated to military-related sectors in countries experiencing violent conflict.

4.2 Loan-level results

In Table 2, we present the estimates from Equation (2). As in Table 1, we start with a parsimonious model and then gradually add fixed effects. In column (1), we only use bank fixed effects, firm fixed effects, and interactions of home-country and host-country dummies with year dummies. The evidence shows that in non-conflict times, the average foreign loan is smaller than the average domestic loan, and that in times of conflict cross-border loans shrink even further, by $e^{-0.224} - 1$, or by about 20.1 percent.

In column (2), we add the double interactions of $Foreign$ and $Military$ and of $Conflict$ and $Military$, as well as the triple interaction of $Foreign$, $Conflict$, and $Military$. The evidence is consistent with what Table 1 documented at the aggregate level: while foreign lending to non-military firms declines when a country experiences a violent conflict, lending to military firms increases significantly.

Table 2. Cross-Border Lending to Military Firms During Violent Conflicts: Loan-Level Analysis

Dependent variable	$Loan_{bfsct}$		
	(1)	(2)	(3)
Foreign	-0.085***	-0.090***	
	(0.010)	(0.010)	
Foreign × Conflict	-0.224*	-0.319***	-0.310***
	(0.116)	(0.115)	(0.115)
Foreign × Military		0.027***	
		(0.008)	
Foreign × Conflict × Military		0.509***	0.522***
		(0.105)	(0.105)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Conflict × Military FE		✓	✓
Foreign × Military FE			✓
Military × Year FE			✓
Foreign × Year FE			✓
N obs	1,308,048	1,308,048	1,308,048
N of banks	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2). The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). All regressions include fixed effects as specified. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank are shown in parentheses.

We continue to obtain very similar effects, both in terms of statistical significance and in terms of economic magnitude, once we add the double interactions of the $Military$ dummy and the *Foreign* dummy, as well as of both dummies with year dummies (column 3). In this most saturated and preferred specification, we find that relative to domestic lending, foreign lending to a firm in the non-military sector declines by $e^{-0.310} - 1$, or by about 26.7 percent, while foreign lending to a firm in the military sector increases by $e^{(0.522-0.310)} - 1$, or by 23.6 percent, again relative to domestic banks. We note that the explanatory power of the regression is quite high, at about 87%.

Our headline results reveal two contrasting effects of violent conflicts on cross-border lending. While foreign lending declines to countries experiencing conflict—consistent with the "flight home" effect documented in the empirical banking literature—this overall reduction stems exclusively from a retrenchment in lending to non-military firms. In contrast, cross-border lending to military-related firms increases substantially.

4.3 Robustness

We now verify whether our baseline findings are robust to the use of different sample selections and variable definitions.

Conflict definition. In Appendix Table J.I, we re-run Equation (2) while defining the variable *Conflict* using different casualty thresholds. Recall that our baseline specification, reproduced in column (6), applies a cut-off of at least a 1,000 deaths per year. We now reconstruct this variable using different thresholds: more than 0, 100, 250, 500, or 750 annual deaths (columns 1-5). We find no difference in the response of domestic and foreign banks' lending to non-military firms when *Conflict* is defined using a relatively low threshold (less than 500 violent deaths, columns 1-4). It is only when conflicts get more violent (i.e., for a threshold of 750 violent deaths) that we start to observe a larger decline in lending by foreign banks to non-military firms in a country in conflict, relative to domestic banks. That is, cross-border lenders initiate broad-based capital retrenchment only when hostilities intensify to high-casualty levels.

In contrast, we find a statistically significant increase in foreign lending to military firms, relative to domestic lending, for *all* conflict intensities (columns 1-5). Importantly, however, the magnitude of this effect increases with the death threshold used, suggesting that the more violent the conflict, the more likely foreign banks are to increase lending to military firms. Numerically, when we use a threshold of 500 deaths to define the variable $Conflict$, the effect is already in the ballpark of the estimate from the preferred specification in Table 2, column (3)—which we replicate in column (6) of Appendix Table J.I. The estimates reported in Table J.I thus imply that both the "running for the exit" effect and the propensity to reallocate lending to military firms increase with the severity of the violent conflict.

In Appendix Table J.II, we run a version of the same exercise by replacing the dummy variable $Conflict$ with the continuous measure of fatalities, conditional on fatalities being higher than a pre-defined threshold. We confirm the findings from Appendix Table J.I, namely that foreign lending to military firms increases with the severity of the conflict, with the largest increase observed beyond a threshold of 500 violent deaths.

Defining military sectors. In Appendix Table K.I, we check whether our main results do not depend on one particular classification of firms into "military" versus "non-military". Recall that in our main test, we classify firms as "military" if their primary, secondary, or tertiary SIC code belongs to the list of 89 military sectors in Table D.I (we replicate these results in column 1). However, most of these sectors produce dual purpose goods. We therefore now split these sectors into "dual-use" and "primary military use" (79 and 10 sectors, respectively). We find that during violent conflicts, cross-border lenders start to lend relatively more to both producers of dual-use goods (column 2) and of primary military goods (column 3). The latter column shows that the main effect we document is not an artifact of cross-border lending increasing to firms that produce mostly non-military goods.

Loan composition and syndicate structure. In Appendix Table L.I, we perform several robustness tests related to missing loan shares and the heterogeneity of syndicates and loan types. Column (1) shows our baseline approach, in which we impute missing shares using each bank's historical average share from loans with known allocations and then reweigh these shares so that they add up to 100%. In column (2), following De Haas and Van Horen (2013), we split each loan tranche equally among all syndicate participants when the actual shares are not known. Our results are robust to using this alternative approach to calculate loan shares. Next, we keep only those loans where the number of lead arrangers is less than or equal to 5 (column 3) or 10 (column 4). We continue to obtain statistically significant estimates of both β_1 and β_3. Finally, we keep only common loan types (i.e., term loans and credit lines), consistent with Wix (2023) (column 5) or only loans that are not extended for a takeover or acquisition, consistent with Chakraborty, Goldstein and MacKinlay (2018) (column 6). In both cases, our results continue to hold.

Country sample. In Appendix Table M.I, we check whether our results may be driven by a handful of source countries. To that end, we exclude from the sample large and important countries, both economically and in terms of overall number of loans: the United States, Japan, Germany, France, China, or the UK. This exercise confirms that our results are not driven by specific countries. We continue to find statistically and economically significant results when excluding loans from banks in the United States (32.8% of observations, column 1); Japan (15.3%, column 2); Germany (6.3%, column 3); France (6.0%, column 4); China (2.7%, column 5); or the UK (6.0%, column 6).

Keeping only the largest cross-border lenders. In Appendix Table N.I, we demonstrate that even when the sample is drastically reduced to the 575 largest global syndicated lenders (i.e., those with at least 300 recorded loan tranches), our baseline results remain consistent. This indicates that our results are not driven solely by numerous small lenders that issue only a few loans each.

4.4 Supply, demand, and bank-firm relationships

Our evidence so far indicates that violent conflict leads cross-border lenders to increase their credit exposure to the military sector relative to domestic banks, while simultaneously reducing their non-military lending to the affected country. But are these effects driven by an increase in credit supply, in credit demand, or both?[8] We now run several tests in the spirit of Khwaja and Mian (2008) to help answer this question. The idea is to exploit two salient features of the syndicated loan market. First, the same bank typically lends to multiple firms within a short time period, and so by including interactions of bank and year fixed effects, we can hold bank-specific credit supply constant. Analogously, firms in the same country–sector receive multiple loans at the same point in time, and so by including interactions of host country, military sector, and year fixed effects, we can hold demand constant at the country–sector–year level.

Table 3 reports estimates from this version of Equation (2). Columns (1)–(3) present our baseline approach, while columns (4)–(6) also include bank × firm fixed effects to control for time-invariant relationship characteristics.[9] Importantly, in columns (2) and (5), we saturate the model with bank × year fixed effects to hold credit supply constant, allowing us to isolate demand-side effects. Conversely, columns (3) and (6) include host country × military sector × year fixed effects to control for shocks to country-sector credit demand.

We find that the increase in military-sector lending during conflicts persists when controlling for supply factors—columns (2) and (5)—with the coefficient on the triple interaction remaining positive and significant. The economic magnitude is approximately 13.5% larger in column (2) compared to the baseline specification in column (1), and 18% larger in column (5) compared to column (4) when accounting for bank-firm relationships. However, in both

[8]A straightforward way to tackle this question is to look at the evolution of interest rates on loans to military firms, compared with non-military loans, in conflict versus non-conflict countries. Unfortunately, the data on interest rate spreads are too incomplete to make such a test possible. Although interest rate data are available for 38.3% of US loans, they exist for only 1.7% of non-US loans.

[9]In columns (4)–(6), the number of observations declines by around half as we lose all non-repeat bank-firm credit relationships.

Table 3. Loan-Level Analysis of Cross-Border Lending to Military Firms During Violent Conflicts: Supply, Demand, and Bank-Firm Relationships

Dependent variable	$Loan_{bfsct}$					
	Baseline	Demand	Supply	Baseline	Demand	Supply
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.310***	-0.248	-0.272**	-0.466*	-0.297	-0.396*
	(0.115)	(0.154)	(0.111)	(0.248)	(0.328)	(0.203)
Foreign × Conflict × Military	0.521***	0.590***	0.100	0.551**	0.653**	0.053
	(0.105)	(0.105)	(0.131)	(0.235)	(0.259)	(0.360)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓	✓	✓
Bank × Year FE		✓			✓	
Host Country × Military × Year FE			✓			✓
Bank × Firm FE				✓	✓	✓
N obs	1,308,048	1,273,395	1,307,976	690,405	664,711	690,213
N of banks	14,021	10,761	14,021	6,721	2,820	6,719
R^2 (adj.)	0.868	0.873	0.869	0.894	0.898	0.896

Note: This table shows the results from estimating Equation (2). The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). All regressions include fixed effects as specified. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank are shown in parentheses.

cases, the point estimate of β_1 is not statistically significant. Conversely, when we control for country-sector demand in columns (3) and (6), the coefficient for β_3 becomes statistically insignificant, while the β_1 estimate remains negative and significant.

Taken together, these patterns indicate that the increase in foreign military lending during conflicts is primarily due to the heightened demand of defense firms that foreign banks are better positioned to meet, rather than from foreign banks proactively targeting these sectors. Meanwhile, the broader reduction in foreign bank exposure to conflict countries is observed net of demand factors, consistent with a classic supply-driven "flight home" effect.

4.5 Geopolitical alignment and cross-border lending

We now extend our analysis by examining the geopolitical distance between a bank's headquarters country and destination countries. Our aim is to analyze whether in conflict times, banks align lending practices with their home country's geopolitical interests, particularly in military-related financing. Anecdotal evidence suggests that while Western banks typically prioritize profit motives, non-Western institutions, often publicly-owned, may emphasize government interests more. We classify countries in two ways: through formal membership in well-defined geopolitical blocs and by using United Nations (UN) General Assembly voting data from Bailey, Strezhnev and Voeten (2017) to identify geopolitical alignments based on shared values. We then replace the variable $Foreign$ in Equation (2) with dummies for different types of geopolitical orientation. We do so in two ways, first by simply distinguishing between the countries where banks are domiciled, and then by also accounting for the geopolitical proximity between these countries and those where borrowing firms are located.

4.5.1 Geopolitical and military country blocs

Table 4 reports the results of tests where we distinguish only between the creditors' countries. The first meaningful way in which countries sort themselves on geopolitical grounds is by their membership in formal geopolitical organizations or more informal forums. These structures may be military or political, but in both cases they reveal, by means of participation in actual treaties, the geopolitical bend of their members.

We use two such groupings. The first is BRICS vs NATO countries. BRICS is a loose organization of important emerging markets representative of the so-called "Global South", namely Brazil, Russia, India, China, and South Africa. NATO, on the other hand, is a western defense alliance encompassing at present 32 countries in Europe and North America (Finland's and Sweden's recent additions are outside of our time period, and for one country,

Table 4. Geopolitical Origin and Cross-Border Lending During Violent Conflicts

	Dependent variable: $Loan_{bft}$		
Country bloc B_1:	BRICS	BRICS	West UN
Country bloc B_2:	NATO	G7	East UN
Country bloc B_3:	Others	Others	Neutral
	(1)	(2)	(3)
Conflict × B_1 Foreign	-0.234**	-0.231**	-0.333***
	(0.111)	(0.113)	(0.122)
Conflict × B_2 Foreign	-0.289**	-0.297***	-0.349***
	(0.114)	(0.115)	(0.121)
Conflict × B_3 Foreign	-0.264**	-0.241**	-0.294**
	(0.110)	(0.109)	(0.128)
Conflict × Military × B_1 Foreign	0.423***	0.423***	0.494***
	(0.108)	(0.106)	(0.110)
Conflict × Military × B_2 Foreign	0.507***	0.498***	0.578***
	(0.158)	(0.158)	(0.140)
Conflict × Military × B_3 Foreign	0.642***	0.617***	0.585***
	(0.100)	(0.107)	(0.125)
Bank FE, Firm FE	✓	✓	✓
Home (Host) Country × Year FE	✓	✓	✓
Military × Year FE	✓	✓	✓
Conflict × Military FE	✓	✓	✓
Foreign (B_1, B_2, or B_3) × Military FE	✓	✓	✓
Foreign (B_1, B_2, or B_3) × Year FE	✓	✓	✓
N obs	1,308,048	1,308,048	1,308,048
N banks	14,021	14,021	14,021
R^2 (adj.)	0.867	0.868	0.868
N countries in bloc B_1	5	5	52
N countries in bloc B_2	29	7	48
N countries in bloc B_3	122	145	86

Note: The dependent variable is the natural logarithm of the loan amount. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). In columns (1), country blocs B_1, B_2, and B_3 distinguish between banks headquartered in BRICS vs. NATO vs. all other countries. Column (2) does the same but replaces NATO with G7. In column (3), we use Bailey et al. (2017) to divide countries into a West or East bloc depending on the country's voting behavior on UN Resolutions. *West Foreign* (*East Foreign*) is a dummy variable equal to one if the loan is extended by a bank from a country leaning towards the West (East) bloc to a firm domiciled in a foreign country. Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

Montenegro, there are no DealScan data). The remaining 122 countries are classified as "Others". The evidence in column (1) suggests that banks from all three groups tend to increase military lending to a foreign country that is experiencing a violent conflict. Although the effect is largest for banks from non-BRICS, non-NATO countries, and smallest for banks from the BRICS, in all three cases the effect is significant at the 1% statistical level.

In column (2), we compare BRICS to the G7 instead of NATO. The G7 was formed in 1975 to include what were at the time the seven largest economies, all of them liberal democracies: the United States, Japan, Germany, the United Kingdom, France, Canada, and Italy. Thus, it represents another bloc of large economies aligned with the west.[10] In this test, a total of 145 countries are classified as "Others". Once again, the evidence indicates that all foreign banks increase lending to military firms in conflict countries. As in column (1), the effect is numerically strongest for banks domiciled in the category "Others", but the effect is again significant at the 1% statistical level for all three groups.

4.5.2 West vs. East political orientation in UN voting

Our second approach is to categorize countries into hypothetical Western, Eastern, or non-aligned blocs without resorting to formal club membership. We rely on a measure of geopolitical distance derived from voting patterns at the United Nations General Assembly (UNGA). Bailey et al. (2017) construct the ideal point distance, which quantifies countries' foreign policy alignment with the US-led liberal order. This measure allows us to track changes in state preferences over time independent of changes in the UN agenda. Variations in these ideal points highlight whether states' foreign policy positions are converging or diverging.

We take the difference of the ideal points between any country and the US and then assign countries to quartiles based on this difference. Those in the bottom quartile (i.e., closest to the US) are defined as "West UN", those in the top quartile (i.e., farthest from the US) as

[10] Russia was included in what became the G8 in 1997 and expelled in 2014 following the annexation of Crimea.

"East UN", and those in the middle two quartiles as "Neutral".[11] This method ensures that the blocs are mutually exclusive at any given point in time while allowing countries to change their geopolitical bend over time (e.g., based on its UN voting pattern, Russia is classified as "West UN" during the 1990s and early 2000s and as "Neutral" after the mid-2000s).

Column (3) of Table 4 reports results using this time-varying geopolitical classification. The evidence indicates that foreign banks significantly increase lending to military firms in conflict countries relative to domestic banks, regardless of their home country's geopolitical orientation. However, the magnitude varies meaningfully across blocs: banks domiciled in "Neutral" countries increase lending by a quarter more than those domiciled in "UN-West" countries (an increase of 79.5 vs. 63.9 percent)

4.5.3 Geopolitical alignment between countries of creditor and borrower

We now test whether the geopolitical alignment between creditor and borrower country affects the credit allocation to military firms in conflict countries. The idea is similar to the approach in Kempf et al. (2023), who find that the ideological alignment of US institutional investors with foreign governments affects their cross-border capital allocation. We modify Equation (2) by replacing the variable $Foreign$ with dyadic dummies for different types of geopolitical alignment. We classify both creditor and borrower countries into "UN West", "UN East", or "Neutral" groups using the same methodology as above, then create nine dyadic combinations representing all possible creditor-borrower geopolitical alignments.[12]

In column (1) of Table 5, we report a version of Equation (2) where we account for whether banks from UN-West countries tend to increase lending to military firms in conflict countries, depending on whether the conflict country is in "UN West", "UN East", or "Neutral". We find that western banks increase lending significantly to military firms in eastern and in neutral conflict countries by 103.0 and 75.8 percent, respectively, while they *reduce* lending

[11] As an additional robustness check, we construct terciles where the geopolitical alignment of each country is again allowed to vary over time. The results remain consistent.

[12] Appendix Tables O.I–O.III report the country composition of these dyads based on time-varying UN voting patterns during 1989–2020.

Table 5. Geopolitical Alignment and Cross-Border Lending During Violent Conflicts

	Dependent variable: $Loan_{bft}$		
Country bloc dyad B_{i1}:	*West* to West	*Neutral* to West	*East* to West
Country bloc dyad B_{i2}:	*West* to Neutral	*Neutral* to Neutral	*East* to Neutral
Country bloc dyad B_{i3}:	*West* to East	*Neutral* to East	*East* to East
	$i = 1$	$i = 2$	$i = 3$
Conflict × B_{i1} Foreign	-0.538***	-0.034	-0.238
	(0.135)	(0.149)	(0.175)
Conflict × B_{i2} Foreign	-0.348***	-0.312**	-0.367***
	(0.126)	(0.130)	(0.121)
Conflict × B_{i3} Foreign	-0.361**	-0.259	-0.315**
	(0.150)	(0.161)	(0.155)
Conflict × Military × B_{i1} Foreign	-0.389***	n/a	n/a
	(0.137)		
Conflict × Military × B_{i2} Foreign	0.541***	0.564***	0.695***
	(0.120)	(0.134)	(0.158)
Conflict × Military × B_{i3} Foreign	0.708***	0.482**	-0.028
	(0.241)	(0.215)	(0.282)
Bank FE, Firm FE	✓	✓	✓
Home (Host) Country × Year FE	✓	✓	✓
Military × Year FE	✓	✓	✓
Conflict × Military FE	✓	✓	✓
Foreign (West, Neutral, or East) × Military FE	✓	✓	✓
Foreign (West, Neutral, or East) × Year FE	✓	✓	✓
N obs	1,308,048	1,308,045	1,308,047
N banks	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868
N home/(conflict) host countries in dyad bloc B_{i1}	30/4	17/4	8/4
N home/(conflict) host countries in dyad bloc B_{i1}	36/10	40/10	24/10
N home/(conflict) host countries in dyad bloc B_{i2}	19/10	17/10	18/10

Note: The dependent variable is the natural logarithm of the loan amount. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). We use Bailey et al. (2017) to divide countries into a West, East, or Neutral bloc depending on the country's voting behavior on UN Resolutions from 1989 to 2020. We create nine dyads tracing where the credit is coming from (a foreign bank from either West, Neutral, or East) and where it arrives in (a firm in a country that experiences violent conflict in West, Neutral, or East). B_{ij} *Foreign* is a dummy variable equaled to one if the loan is extended by a bank from a country leaning towards bloc i (which is West in column 1, Neutral in column 2, and East in column 3) to a firm domiciled in a country from bloc j ($i, j = 1, 2, 3$; if $i = j$, we additionally require bank and firm to be located in different countries). Each column also contains the estimates on the Conflict × Foreign and Conflict × Military × Foreign variables for the foreign lenders originating from the other country blocs—Neutral and East in column (1), West and East in column (2), and West and Neutral in column (3)— and lending to firms in any of the three blocs. We do not report these coefficients to preserve space. Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

to military firms in western conflict countries by 32.2 percent. This contrasting result may reflect geopolitical considerations, where western banks may face regulatory constraints, reputational concerns, or policy pressures that discourage financing military activities in allied nations during conflicts, while having greater flexibility to pursue profit opportunities in non-aligned or politically distant countries.

Column (2) examines banks from neutral countries, which increase military lending to neutral (75.8 percent) and East UN destinations (61.9 percent) but not to West UN countries (no military deals observed during conflicts). Column (3) focuses on East UN banks, which significantly increase military lending only to neutral destinations—yielding one of the largest effects across all dyads. East UN banks show no response when lending to West UN countries (no deals observed) or to other East UN countries (statistically insignificant effects)

Tables 3 and 4 reveal that geopolitical orientation significantly affects military lending patterns during conflicts. While banks from all regions engage in such lending, the magnitude depends on the destination countries. Banks from all three blocs increase military lending to neutral conflict countries. Conversely, no banks expand military lending to Western conflict countries (Western banks actually decrease it). For Eastern conflict countries, Western banks increase lending more than neutral banks, while Eastern banks show no response.

These findings reveal a consistent pattern: banks preferentially direct military financing toward non-aligned or politically distant countries during conflicts while avoiding such lending to geopolitically similar nations. This suggests that while political alignment matters in normal times (Kempf et al., 2023), conflict creates conditions where profit motives dominate for "out-group" lending, whereas political constraints, allied coordination, or regulatory concerns may limit military financing to aligned countries.

4.6 Bank specialization and cross-border conflict lending

A recent literature documents large differences in lending specialization across banks (Paravisini et al., 2023; Blickle, Parlatore and Saunders, 2024) and finds that these specialization patterns influence banks' lending decisions, especially in times of instability. The possibility therefore arises that our results partly reflect the tendency of some banks to have lending portfolios tilted toward either particular conflict countries or the military sector. To investigate this, we consider two types of specialization: in a country and in a sector.

We measure bank specialization in three steps. First, for each bank b, we compute annual lending shares to foreign country c or sector s in year t as percentages of total lending by bank b across all foreign countries or sectors, respectively:

$$CS_{bct} = \frac{\sum_{f=1}^{F_{bct}} Loan_{bfct}}{\sum_{c=1}^{C_{bt}} \sum_{f=1}^{F_{bct}} Loan_{bfct}}, \quad SS_{bst} = \frac{\sum_{f=1}^{F_{bst}} Loan_{bfst}}{\sum_{s=1}^{S_{bt}} \sum_{f=1}^{F_{bst}} Loan_{bfst}} \tag{3}$$

where CS and SS denote country and sector shares, respectively.

Second, we calculate cumulative average lending shares from each bank's first sample appearance through year t, smoothing year-to-year volatility to capture long-term specialization patterns. Third, we identify specialized banks using relative thresholds. For each conflict country and year, we calculate the 75th percentile of all banks' cumulative lending shares to that country ($\alpha_{vc,t}$) following Paravisini et al. (2023). Banks exceeding this threshold are classified as country-specialized. We apply the same approach for military sector specialization using thresholds $\alpha_{s,t}$:

$$RSFC_{bct} = \begin{cases} 1, \text{ if } Share_{bct} \geq \alpha_{vc,t} \\ 0, \text{ if else} \end{cases} \quad RSMS_{bst} = \begin{cases} 1, \text{ if } Share_{bst} \geq \alpha_{s,t} \\ 0, \text{ if else} \end{cases} \tag{4}$$

where $RSFC$ and $RSMS$ stand for relative specializations in a foreign country and in the military sector, respectively.

We can now estimate Equation (2) separately for specialized and non-specialized cross-border lenders, using domestic lenders as the control group in both cases. Specifically, we compare country-specialized foreign banks ($RSFC_{bct} = 1$) to domestic banks, then compare non-specialized foreign banks $RSFC_{bct} = 0$) to domestic banks. We repeat this analysis for sector specialization, comparing military-specialized and non-specialized foreign banks to domestic lenders. Table 6 reports these results.

Table 6. Bank Specialization and Cross-Border Lending During Violent Conflicts

	Dependent variable: $Loan_{bft}$					
Specialization:	Relative measure (Paravisini et al., 2023)					
	In country ($RSFC_{bct} = 1$)		*P*-value *diff=0*	In sector ($RSMS_{bst} = 1$)		*P*-value: *diff=0*
	Yes	No		Yes	No	
	(1)	(2)		(3)	(4)	
Foreign × Conflict	-0.515***	-0.414***	*0.653*	-0.288**	-0.257**	*0.850*
	(0.178)	(0.137)		(0.119)	(0.112)	
Foreign × Conflict × Military	0.124	0.404***	*0.115*	0.399***	-0.042	*0.024*
	(0.128)	(0.123)		(0.108)	(0.162)	
Bank FE	✓	✓		✓	✓	
Firm FE	✓	✓		✓	✓	
Home Country × Year FE	✓	✓		✓	✓	
Host Country × Year FE	✓	✓		✓	✓	
Conflict × Military FE	✓	✓		✓	✓	
Foreign × Military FE	✓	✓		✓	✓	
Military × Year FE	✓	✓		✓	✓	
Foreign × Year FE	✓	✓		✓	✓	
N obs	718,347	1,277,623		1,279,107	1,085,294	
N banks	10,605	13,767		13,885	13,165	
R^2 (adj.)	0.911	0.869		0.868	0.866	

Note: This table shows the results of our baseline specification (2) run on four sub-samples of banks: those specialized in lending to particular countries ($RSFC_{bct} = 1$) and those that are not ($RSFC_{bct} = 0$), in the first two columns, and those specialized in lending to military firms ($RSMS_{bst} = 1$) and those that are not ($RSMS_{bst} = 0$), in the last two columns. In all cases, the dependent variable is the natural logarithm of the loan amount. Relative specialization measures are used, cf. expressions (4), with the cutoff thresholds $\alpha_c = \alpha_s = 75^{th}$ percentile, which correspond to 3.9% of the bank-country lending share and 19.3% of the bank-sector lending share. *Foreign* is a dummy equal to one if the bank lends to a firm in another country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). All regressions include fixed effects as specified. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank are shown in parentheses.

The first two columns of Table 6 reveal distinct patterns based on country specialization. Cross-border lenders specialized in conflict-affected countries show minimal increases in military lending during conflicts (column 1). In contrast, non-specialized cross-border lenders drive our baseline results, expanding military lending approximately four times more intensively than their specialized counterparts, though this difference is marginally significant (p-value = 0.115). Both groups similarly reduce non-military lending during conflicts.

These findings suggest divergent strategies. Country-specialized banks exhibit a flight-home effect, reducing both military and non-military lending as they retreat from familiar but now-risky markets. Non-specialized banks, however, aggressively reallocate capital toward military sectors while maintaining similar reductions in non-military lending, consistent with profit-seeking in unfamiliar markets where they may face fewer reputational constraints.

Columns (3) and (4) of Table 6 reveal the opposite pattern for military sector specialization. Banks with higher pre-conflict specialization in military lending significantly increase their defense-sector exposure during conflicts, while non-specialized banks reduce it (p-value = 0.024). Both groups similarly contract their non-military lending. This pattern suggests that military-specialized banks leverage their established expertise to further reallocate portfolios to defense sectors during conflicts. In contrast, banks without military specialization avoid increasing defense exposure, possibly due to lack of sector-specific knowledge or relationships that would enable them to capitalize on conflict-driven opportunities.

Overall, these results underscore how preexisting geographical and sector expertise shape banks' lending responses during armed conflicts. They strongly suggest that the increase in military lending during violent conflicts is driven by foreign banks that are relatively more specialized in military lending and that accommodate the rising demand for credit by military firms in countries vis-à-vis which they do not have prior expertise.

5 Extensions

5.1 Spillovers to neighboring countries?

We explore whether banks increase military lending to neighboring countries not directly involved in conflicts, testing for potential spillover effects. Wars can impact regional security dynamics (Federle, Meier, Müller, Mutschler and Schularick, 2024), leading neighboring states to strengthen their defense capabilities in response to heightened geopolitical uncertainty. This could increase the demand for military equipment in adjacent countries, potentially prompting cross-border lenders to expand military credit beyond the primary conflict zone.

We take this question to the data by first identifying the neighbors of countries in conflict as identified in Table A.I. We do this manually and are careful to exclude the observations where neighboring countries are in major conflicts themselves (i.e., those above the 1,000 battlefield deaths threshold). For instance, Pakistan cannot serve as a neighboring country for India, and vice versa, in 2008, 2009, and 2010 since both countries experienced major conflicts in these years, even though they serve as neighbors in non-conflict years. Hence, we want to examine whether cross-border military lending to a neighboring country increases only because its neighbor is involved in a major violent conflict.

In Table 7, we examine potential spillover effects by modifying our baseline specification. We create a new variable, $Neighbor$, which equals one for countries that share a border with a conflict-affected nation but do not themselves experience major conflict in that year. We apply increasingly stringent definitions of "non-conflict" across columns: column (1) includes neighboring countries with fewer than 1,000 battlefield deaths, while column (4) restricts the sample to neighboring countries with zero battlefield deaths. This approach allows us to isolate the pure spillover effect from any direct conflict impact.

The results are consistent across specifications: cross-border lenders do not increase military lending to neighboring non-conflict regions. We interpret these results as an indication

Table 7. Cross-Border Lending During Violent Conflicts: Spillovers

	Dependent variable: $Loan_{bft}$			
Neighboring countries:	Countries with N *deaths* $\leq j$:			
	$j = 1,000$	$j = 500$	$j = 100$	$j = 0$
	(1)	(2)	(3)	(4)
Neighbor × Foreign	-0.026	-0.050	-0.097***	-0.101***
	(0.037)	(0.033)	(0.036)	(0.038)
Neighbor × Foreign × Military	0.065	-0.043	-0.020	-0.024
	(0.043)	(0.041)	(0.038)	(0.040)
Bank FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓
N obs	1,308,048	1,308,048	1,308,048	1,308,048
N of banks	14,021	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2) with a focus on the neighbors of conflict countries. The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Neighbor* is a dummy equal to one if the firm is located in a country bordering on a conflict country. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for SIC codes). Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

that banks are reactive, but not proactive in their military lending decisions. Columns (3) and (4) also indicate that cross-border lenders reduce their non-military lending to neighboring countries with very low or no conflict intensity. However, we find no corresponding increase in military-sector lending to these neighboring countries, suggesting that foreign banks' strategic military financing is specifically targeted to primary conflict zones rather than extending to regional neighbors experiencing spillover instability.

5.2 Cross-border lending during post-conflict recoveries

Our baseline specification treats pre- and post-conflict years equally in the reference category. However, post-conflict years may be distinct, as banks face competing incentives regarding military lending. Banks may continue military financing if peace appears fragile or to strengthen defense capabilities against future conflicts. Conversely, they may reduce military lending due to diminished defense sector profitability relative to reconstruction opportunities, or because peace agreements reduce government demand for military equipment and impose new regulatory constraints on defense financing.

We define a new dummy variable $Post\text{-}Conflict$ that is equal to 1 in the first, second, or third year after the end of hostilities. In Table 8, we report a version of Equation (2) that includes this variable instead of $Conflict$. We find that lending to the military sector in the first year after the end of a violent conflict is still significantly higher for foreign banks than for domestic banks (column 1). However, the effect becomes substantially weaker, both economically and statistically, in the second year after the conflict (column 1). Finally, during the third year after the conflict, the difference in lending to the military sector between domestic and foreign banks disappears completely (column 3). These findings align with the temporal patterns shown in Figure 2, which demonstrates that the military lending effect peaks during the conflict period and gradually dissipates in subsequent years.[13]

Our results indicate that foreign banks' military lending advantage is temporally bounded, concentrated during active conflict periods when defense demand peaks and domestic financial capacity is most constrained. Conversely, the coefficient on $Post\text{-}Conflict \times Foreign$ becomes increasingly positive over time, reaching statistical significance in the third post-conflict year (column 3). This pattern suggests foreign banks gradually re-enter conflict-affected markets by expanding non-military lending as reconstruction opportunities emerge, effectively reversing their initial flight-home behavior.

[13]These estimates do not change materially when we also include the double and triple interaction terms with $Conflict$.

Table 8. Cross-Border Lending After Violent Conflicts

	Dependent variable: $Loan_{bft}$		
Post-conflict period:	One year	Two years	Three years
	(1)	(2)	(3)
Post-Conflict × Foreign	0.036	0.157	0.258**
	(0.147)	(0.135)	(0.114)
Post-Conflict × Foreign × Military	0.724***	0.423**	-0.012
	(0.169)	(0.190)	(0.172)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Conflict × Military FE	✓	✓	✓
Foreign × Military FE	✓	✓	✓
Military × Year FE	✓	✓	✓
Foreign × Year FE	✓	✓	✓
N obs	1,308,048	1,308,048	1,308,048
N banks	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2) with a focus on the post-conflict period. The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Post-Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

5.3 Geographical distance to violent conflicts

While countries proximate to conflict zones may suffer economic hardship, those at a greater distance may experience some economic gains, as they can take advantage of the increased returns from military activities without bearing the direct costs of conflict (Federle et al., 2024). This geographic dynamic creates two competing hypotheses regarding military lending: banks from distant countries may be better positioned to capitalize on increased military credit demand due to their insulation from conflict risks, while banks from neighboring countries may have an advantage due to superior information about potential borrowers.

In Table 9, we examine these competing hypotheses by replacing the *Foreign* dummy with a continuous variable: the log distance between capital cities (set to zero for domestic banks). Column (1), which excludes the triple interaction, tests whether the "flight home" effect strengthens with geographical distance. Our results confirm this intuitive relationship: cross-border lending to the conflict country declines more as the distance from the conflict zone increases. In columns (2) and (3), this effect becomes statistically significant. Yet, columns (2) and (3) also reveal an inverse pattern for military lending, whereby the effect strengthens with greater geographical distance between bank and borrower.

Table 9. Geographical Distance and Cross-Border Lending During Violent Conflicts

Dependent variable	$Loan_{bft}$		
	(1)	(2)	(3)
Distance	-0.010***	-0.011***	-0.005
	(0.001)	(0.001)	(0.005)
Distance × Conflict	-0.018	-0.029**	-0.028**
	(0.013)	(0.013)	(0.013)
Distance × Military		0.003***	0.005
		(0.001)	(0.004)
Distance × Conflict × Military		0.056***	0.057***
		(0.012)	(0.012)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Conflict × Military FE		✓	✓
Foreign × Military FE			✓
Military × Year FE			✓
Foreign × Year FE			✓
N obs	1,306,499	1,306,499	1,306,499
N of banks	13,981	13,981	13,981
R^2 (adj.)	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2) with a focus on the geographical distance between the domicile country of the bank and the firm. The dependent variable is the natural logarithm of the loan amount. *Distance* is the natural logarithm of the geographical distance between a foreign lender's home country and borrowing firm's country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). Fixed effects as specified. Data sources: UCDP, DealScan, and CEPII GeoDist. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

This effect is robust across specifications, as we progressively saturate the regression model with fixed effects. The coefficient of 0.057 in the preferred specification in column (3) means that lending to a military firm in a conflict country increases by about 9.4 percent more for a bank domiciled in a country whose capital is 2,000 kilometers from that of the conflict country, relative to a bank that is just 1,000 kilometers away.

This positive triple interaction effect aligns with the idea that geographically distant banks face fewer reputational and regulatory constraints when financing military projects in faraway conflict zones. Banks operating at greater distances may experience less scrutiny from their domestic public, regulatory authorities, and media regarding their financing of military activities. This relative isolation from stakeholder pressure may enable distant banks to more aggressively pursue profit opportunities in conflict-zone military sectors, while their peers in nearby countries face more public scrutiny.

5.4 The role of lender type and bank ownership

A natural extension of our analysis concerns the distinction between bank and non-bank institutions, though the expected differences are theoretically ambiguous. Banks—especially large multinational ones—typically have access to deeper internal capital markets, enabling rapid reallocation of financial resources to areas of peak demand. However, banks also face stricter capital regulations than non-bank institutions, and regulators may be reluctant to permit bank lending to military firms in conflict countries given the risks involved.

Bank ownership represents another important dimension of comparative analysis. An extensive literature demonstrates that public and private banks exhibit distinct lending patterns, often due to political influences—a phenomenon documented in both developed and emerging economies (e.g., Claessens, Feijen and Laeven, 2008; Bircan and Saka, 2021; Koetter and Popov, 2021). If political incentives drive military sector lending, state-owned banks may be more responsive to these pressures than their private counterparts. This raises the possibility that our findings on foreign bank behavior might be primarily explained by their

Table 10. Cross-border Lending During Violent Conflicts:
The Role of Lender Type and Bank Ownership

Dependent variable		$Loan_{bft}$	
$\mathbb{X}_{1,bft}$ $\mathbb{X}_{2,bft}$		Foreign bank Foreign nonbank	Foreign private Foreign public
		(1)	(2)
Conflict × $\mathbb{X}_{1,bft}$	β_{11}	-0.305***	-0.225**
		(0.115)	(0.091)
Conflict × $\mathbb{X}_{2,bft}$	β_{12}	-0.057	-0.205**
		(0.144)	(0.094)
Conflict × Military × $\mathbb{X}_{1,bft}$	β_{21}	0.322***	0.332***
		(0.088)	(0.092)
Conflict × Military × $\mathbb{X}_{2,bft}$	β_{22}	0.414*	0.252**
		(0.223)	(0.111)
Bank FE		✓	✓
Firm FE		✓	✓
Home Country × Year FE		✓	✓
Host Country × Year FE		✓	✓
Conflict × Military FE		✓	✓
Foreign × Military FE		✓	✓
Military × Year FE		✓	✓
Foreign × Year FE		✓	✓
N obs		1,308,048	1,172,768
N lenders		14,021	8,936
R^2 (adj.)		0.868	0.877
Share of $\mathbb{X}_{2,b,f,t}$ in the full sample		10%	8%
P-value of the linear test: $\beta_{11} = \beta_{12}$		*0.012*	*0.673*
P-value of the linear test: $\beta_{21} = \beta_{22}$		*0.660*	*0.338*

Note: The dependent variable is the natural logarithm of the loan amount. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the SIC codes). In column (1), we distinguish between banks and non-banks lending to a firm in a foreign country. In column (2), we distinguish between privately-owned and publicly-owned banks. Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

degree of government ownership. This could also help shed light on the different effects for western and eastern countries that we document in Section 4.5.

In Table 10, we analyze lending patterns across both these dimensions. Column (1) contrasts the behavior of bank versus non-bank creditors. Both groups increase military sector lending in conflict countries relative to domestic creditors, and they do so to a similar extent. At the same time, banks exhibit a stronger flight home effect, and this difference is significant at the 5% statistical level. In column (2), we observe that both private and state-owned banks reduce their lending to the non-military sector in conflict countries, while simultaneously increasing their military sector lending. This suggests that more and less politically aligned creditors respond similarly to the profit opportunities presented by military firms during times of violent conflict.

6 Conclusions

We have investigated how violent conflicts impact cross-border lending, particularly credit allocation to military-related sectors. Leveraging comprehensive data on syndicated loans from 14,021 banks to 97,169 firms across 179 countries over 1989-2020, we establish two key findings. First, the onset of violent conflict leads cross-border lenders to reduce overall credit to a country, relative to domestic banks. This aligns with a flight home effect, whereby foreign lenders are more likely to withdraw from markets experiencing negative shocks. Second, despite this aggregate pullback, cross-border lenders simultaneously increase credit to firms in the conflict country's military sector, compared to domestic banks. This reallocation effect towards military-related industries is economically sizable and robust to varying conflict intensity thresholds, alternative classifications of military sectors, different loan share calculations, and the exclusion of major economies and minor lenders. We show this reallocation stems primarily from heightened demand by defense firms that foreign banks are better positioned to meet, rather than supply-driven targeting of military sectors. In contrast, the flight home effect for non-military lending appears largely supply-driven, reflecting foreign banks' strategic withdrawal from risky markets independent of local demand conditions.

We identify several factors that amplify this military lending effect. It is more pronounced for cross-border lenders with higher relative specialization in military lending, but with less specialized lending portfolios in the conflict country, as well as for those lending to politically non-aligned countries, particularly when banks from Western or Neutral countries direct credit to military firms in non-Western conflict zones. Importantly, we find no evidence of lending spillovers to neighboring countries and the military lending increase dissipates within three years post-conflict, suggesting cross-border lenders take a reactive rather than proactive approach. Our results highlight how global banks act as key capital providers during violent conflicts, significantly shifting credit from civil to military uses. Geopolitical tensions thus emerge as important drivers of international credit reallocation.

Our findings also suggest several promising directions for future research. First, analyzing firm-level data during conflicts could reveal how foreign credit access affects corporate performance and, ultimately, the intensity and duration of hostilities. Second, the interplay between cross-border lending and local banking systems—both domestic banks and foreign subsidiaries—warrants deeper investigation. Third, examining whether banks with strong government ties serve as key nodes in military financing networks could shed more light on the political economy of conflict financing.

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Appendix A Brief descriptions of violent conflicts

Table A.I. Description of violent conflicts, by countries with $\geq$ 1,000 deaths (*beginning*)

Country	Conflict Years	Conflict ID	Conflict Description
Algeria	1998, 1999	386	Since the early 1990s, Algeria has experienced an armed conflict over governmental power, primarily involving various Islamic groups seeking to establish an Islamic state by force. The Algerian Civil War (1992–2002) was marked by intense violence, particularly after the government's decision to cancel the 1991 elections, which an Islamist party was poised to win. The violence peaked in 1993 with widespread massacres and brutality. By 2002, some groups began to disarm and hostilities declined.
Angola	1998, 1999, 2001	327; 387	The Cabindan Insurgency in Angola's Cabinda Province, driven by aspirations for greater autonomy or independence, has been a long-standing conflict, with separatist groups like the Front for the Liberation of the Enclave of Cabinda (FLEC) clashing with the government over the region's substantial oil resources. This insurgency has occurred alongside the Angolan Civil War (1975-2002), a protracted conflict between the People's Movement for the Liberation of Angola (MPLA), which took power after Angola's independence, and opposition groups like the National Union for the Total Independence of Angola (UNITA), supported by the U.S. and apartheid-era South Africa. Rooted in ideological, ethnic, and political tensions, the civil war caused significant loss of life and displacement. It concluded after the death of UNITA leader Jonas Savimbi in 2002, leading to peace and a shift toward national reconciliation.
Colombia	1994, 1996, 1999, 2000, 2001, 2002, 2003, 2004, 2005	289	Colombia's conflict with the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN) spanned decades and centers on issues of land reform, inequality, and government control. The FARC, a Marxist guerrilla group, waged a violent insurgency beginning in the 1960s, leading to widespread violence, drug trafficking, and displacement. A landmark peace agreement in 2016 led to FARC's demobilization and transformation into a political party. The ELN, Colombia's last active guerrilla group, continues armed resistance despite periodic peace talks, focusing on ideological goals of social justice and economic reform.
Congo, DR	2013, 2014	265; 283; 314	The conflict in the Democratic Republic of Congo (DRC) involves a complex mix of internal and external actors, including the Government of the DRC and various rebel groups like Kata Katanga, M23, and the Allied Democratic Forces (ADF). Kata Katanga, a separatist group in the Katanga region, seeks greater autonomy from the DRC, while M23, a Tutsi-led rebel group, accuses the government of failing to implement peace agreements, with some regional backing from Uganda and Rwanda. The ADF, an Islamist militant group from Uganda, has carried out deadly attacks in eastern DRC. Uganda's involvement, sometimes supporting armed groups or intervening directly, has contributed to regional instability.
Ethiopia	2020	267	The Ethiopia-Tigray conflict, which began in November 2020, erupted between the Tigray People's Liberation Front (TPLF) and the Ethiopian government. The TPLF, once part of Ethiopia's ruling coalition, fell out of favor after Prime Minister Abiy Ahmed's rise to power in 2018 and his reforms, which sidelined the TPLF. The conflict escalated when the Ethiopian military launched an offensive in Tigray in response to TPLF attacks on federal military bases. A peace agreement in November 2022 brought a halt to major fighting, but the region remains unstable.
India	1989, 1990, 1991, 1993, 1994, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010	218; 227; 251; 335; 347; 351; 364; 365; 421; 434; 11342; 11475	India became independent in 1947 and a republic in 1950. The country hosts various religions, ethnicities, and tribal groups and this has triggered a variety of armed conflicts over the years. It has especially been the case in India's northeast, where rebel groups based mainly on tribal communities have fought the government in Assam, Tripura, Nagaland, and Manipur. The Indian government has also fought Sikh insurgents over Punjab/Khalistan and various insurgent groups over Kashmir, which is also claimed by Pakistan. Concerning government power, the Indian government has been confronted by several communist groups, such as the MCC, PWG, and CPI-Maoist. The country has also suffered from one interstate conflict with Pakistan over Kashmir.

Table A.I. Description of violent conflicts, by countries with $\geq$ 1,000 deaths (*continuing*)

Iraq	2005, 2006, 2007, 2008, 2009, 2011, 2015, 2017	259; 338	The conflict between the Iraqi government and the Islamic State (IS) escalated in 2014 when IS rapidly captured large swathes of territory in Iraq, including major cities like Mosul, declaring a caliphate. This insurgency sought to establish strict Islamist rule. The Iraqi government, supported by a coalition of international forces, regional militias, and Kurdish Peshmerga, launched a prolonged military campaign to regain control. By late 2017, most of the territory had been recaptured, significantly weakening IS's presence, though sporadic attacks and insurgent activities persist.
Israel	2014	234	The Israel-Palestine conflict is a long-standing conflict with territorial claims over the same land, primarily between Jewish Israelis and Palestinian Arabs. It dates back to the early 20th century and intensified following the establishment of Israel in 1948. Despite numerous peace efforts, the conflict remains unresolved, marked by cycles of violence, occupation of the West Bank, and a blocade of Gaza, as both sides assert rights to self-determination and statehood. In 2014, the conflict between the Government of Israel and Hamas intensified during the Gaza War, also known as Operation Protective Edge. The seven-week military conflict was initiated by escalating tensions and rocket fire from Gaza. The operation involved extensive airstrikes and a ground invasion by Israel aimed at neutralizing Hamas' capabilities.
Liberia	2003	341	From 1999 to 2003, Liberia's government fought against rebel groups, primarily LURD (Liberians United for Reconciliation and Democracy) and MODEL (Movement for Democracy in Liberia), who sought to overthrow President Charles Taylor during the Second Liberian Civil War (1999–2003). The war, which was fueled by political and ethnic divisions, also saw significant regional involvement. The conflict concluded with Taylor's resignation, the signing of the Accra Peace Agreement, and the deployment of a United Nations peacekeeping mission to stabilize the country and facilitate transitional governance.
Nigeria	2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020	297; 13641	Nigeria has been dealing with two major Islamist insurgencies led by the Islamic State West Africa Province (ISWAP) and Jama'atu Ahlis Sunna Lidda'awati wal-Jihad (commonly known as Boko Haram). ISWAP, a faction that split from Boko Haram, operates across Nigeria's northeast and the Lake Chad Basin, seeking to control territory under the banner of the Islamic State's "Greater Sahara Province." Its focus has been on attacking military and civilian targets to establish Islamic governance. Meanwhile, Boko Haram (JAS) has fought to overthrow the Nigerian government since 2009, using terrorism, mass abductions, and violence to enforce its vision of an Islamic state governed by Sharia law.
Pakistan	2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015	218; 325; 404; 418	The conflict involving the Government of Pakistan and al-Qaida, the Balochistan Republican Army (BRA), and Tehrik-i-Taliban Pakistan (TTP) reflects a complex security struggle marked by terrorism, insurgency, and regional instability. Al-Qaida operated within Pakistan following the U.S. invasion of Afghanistan, leading to military actions by both Pakistani and U.S. forces targeting militant strongholds. The TTP, or Pakistani Taliban, has conducted numerous attacks against Pakistani military and civilian targets, seeking to impose strict Islamist rule and undermine the state. Meanwhile, the BRA is a separatist group in Balochistan, engaged in a nationalist insurgency for greater autonomy or independence, often clashing with Pakistani security forces over issues of resource control, human rights, and regional grievances.
Philippines	1990, 1991, 2000, 2003, 2017	209; 308; 14275	The Philippine government has faced long-standing conflicts with the Communist Party of the Philippines-New People's Army (CPP-NPA) and the Moro Islamic Liberation Front (MILF). The CPP-NPA has sought to overthrow the government since the late 1960s through guerilla warfare and political resistance. Meanwhile, the MILF, fighting for autonomy for the Muslim-majority Moro people in the southern Philippines, pursued armed conflict for decades, leading to the 2014 peace deal that established the Bangsamoro Autonomous Region. While the MILF conflict has seen progress through peace agreements, the CPP-NPA insurgency remains a challenge. In addition to conflicts with the CPP-NPA and MILF, the Philippine government has been engaged in fighting against Islamic State (IS)-affiliated groups in the southern Philippines. The conflict intensified in 2017 with the siege of Marawi City, where militants attempted to establish an IS caliphate. Although the siege was ended with government victory, the threat of extremist violence persists through periodic attacks and ongoing insurgency efforts by IS-linked militants.

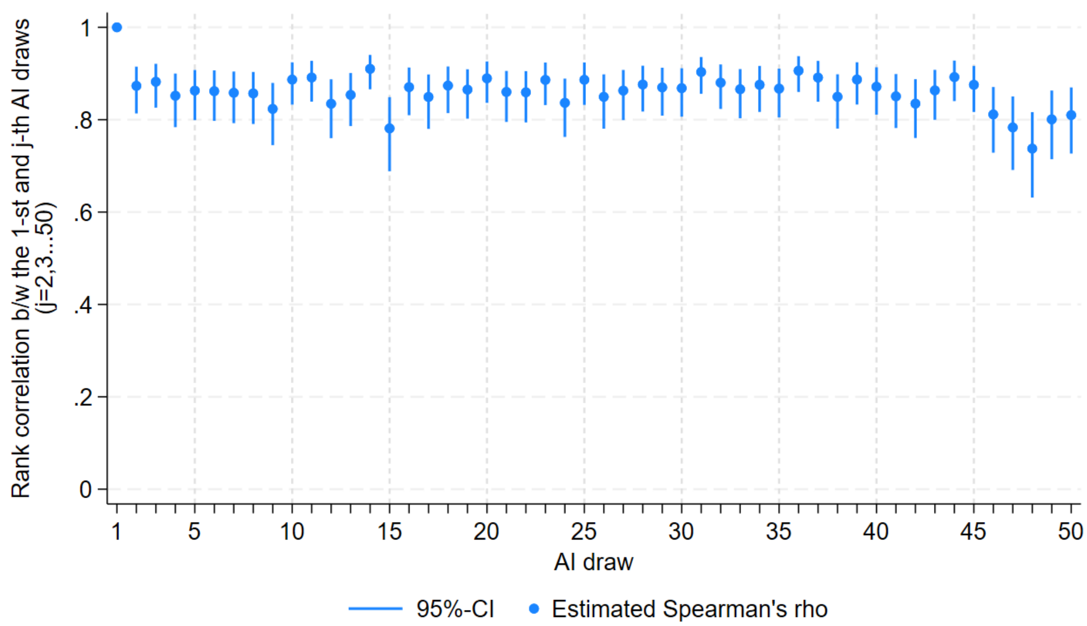
Table A.I. Description of violent conflicts, by countries with $\geq$ 1,000 deaths (*ending*)

Russia	1995, 1996, 1999, 2000, 2002, 2004	401; 414	The conflict between the Russian government and the Chechen Republic of Ichkeria encompasses two wars and ongoing tensions rooted in Chechnya's attempts to gain independence following the Soviet Union's dissolution. The First Chechen War (1994-1996) saw Chechen forces resisting Russian control, eventually achieving a ceasefire and de facto independence. However, the Second Chechen War began in 1999 when Russia reasserted control after a Chechen incursion into Dagestan and a series of bombings attributed to Chechen militants. This conflict led to a large-scale Russian military intervention. By the early 2000s, Moscow had re-established authority, integrating Chechnya more firmly within the Russian Federation under a pro-Russian government, though insurgency and tensions persisted.
Sri Lanka	1995, 1996, 1997, 1998, 1999, 2000, 2001, 2006, 2007, 2008, 2009	352	The conflict between the Sri Lankan government and the Liberation Tigers of Tamil Eelam (LTTE) spanned from 1983 to 2009 and centered on the LTTE's pursuit of an independent Tamil state in the country's north and east. Characterized by intense fighting, bombings, and military offensives, the war concluded in 2009 with the military's victory over the LTTE.
Türkiye	1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2016	338; 354; 383; 13902	The conflict in Türkiye involves the government battling insurgent groups like the PKK (Kurdistan Workers' Party) and DHKP-C (Revolutionary People's Liberation Party/Front), both of which challenge Türkiye 's authority through violent means. The PKK, fighting for Kurdish autonomy since the 1980s, engages in insurgency and is considered a terrorist group by Türkiye , the EU, and the US, while the DHKP-C targets government institutions with terrorism. Both groups have led to significant security responses from Turkey, including military operations and counterterrorism efforts. Additionally, in 2016, ISIS carried out several major attacks in Türkiye , including the deadly Sultanahmet Square bombing in January and the Ataturk Airport bombing in June. These attacks were part of ISIS's broader strategy to destabilize Türkiye , which was actively involved in the fight against the group in Syria and Iraq.
Ukraine	2014, 2015	13219; 13236; 13243; 13247; 13306	The Maidan protests (2013-2014) led to the ousting of Ukrainian President Yanukovych, resulting in political unrest and a shift toward pro-European governance, which was opposed by parts of the population, especially in the eastern regions. In response, Russian-backed separatists in the Donetsk People's Republic (DPR) and Luhansk People's Republic (LPR) declared independence, sparking armed conflict with the Ukrainian government. Russia provided significant military and logistical support to the separatists, while also deploying its own forces in Crimea, which it annexed in 2014.

Note: This table provides an overview of all conflict-affected countries in our dataset, the year(s) in which the death toll exceeded 1,000, the conflict ID(s) from the UCDP dataset, and a short description of the conflict(s) in those particular year(s). The main data source is UCDP, supplemented by background information from Wikipedia and Britannica.

Appendix B AI procedure to identify dual-use sectors

Figure B.I. Rank correlations between different AI-based classification attempts for dual-use sectors



Note: This figure shows the Spearman's rank correlation coefficients between the first and each subsequent request to an AI to assign probabilities of being used for military purposes for each sector of the economy from the UK Strategic Export Control List. Developed by the UK Department for Business and Trade, the UK Strategic Export Control List determines the UK Military List and the UK Dual-Use List, which we use to identify the military and dual-use industries, respectively. From each list, we collect key terms, such as "weapon", "gun", "explosive" for primary military and "nuclear", "electronics", "aircraft", for dual-use, and collect all 4-digit SIC Codes on the NAICS website that would fall under these categories. In this initial process, we collect 10 primary military SIC Codes and 115 dual-use SIC Codes. In a next step, we determine the likelihood of each *dual-use* sector being associated with military functions. For this procedure, we make requests to AI to get familiar with the UK Export Control List and assign likelihoods to each dual-use SIC Code to be used for military purposes. As a check, we discreetly include the 10 primary military SIC codes as "pseudo" dual-use to validate the assessment (AI indeed always assigned a 95-100% probability to those). As the AI procedure is based on expert judgments, we repeat the procedure 50 times, with all 125 SIC codes randomized before each iteration to ensure robustness.

Appendix C Variables definition and sources

Table C.I. Definitions of variables in the regression analysis

Variable	Definition	Source	Unit
Main Variables			
Loan Amount	Loan amount aggregated to the bank-firm-year level	DealScan	Log $US
Foreign	*Dummy* = 1 if country of the bank $\neq$ the country of the firm	Authors' calculations	0/1
Military	*Dummy* = 1 if the firm's Primary, Secondary, or Tertiary SIC code equals the SIC code in Table D.I.	DealScan, NAICS/SIC website & Authors' calculations	0/1
Battlefield Deaths	Battle-field related deaths per country and year. Sum of the 'best' estimate	Uppsala Conflict Data Program (UCDP)	Persons
Conflict (500)	*Dummy* = 1 if battle-field related deaths per country and year are greater or equal to 500.	UCDP & Authors' calculations	0/1
Conflict (1,000)	*Dummy* = 1 if battle-field related deaths per country and year are greater or equal to 1000.	UCDP & Authors' calculations	0/1
Interest rate spread	Spread over default base on the loan	DealScan	Log bps
Loan maturity	Maturity on the loan	DealScan	Log months
Absolute specialization in conflict country	Average (across all years) share of an ever-conflict country in a bank's loan portfolio exceeding the 75^{th} percentile of the corresponding bank-(conflict) country shares' distribution	DealScan & Authors' calculations	0/1
Absolute specialization in military sector	Average (across all years) share of the military-related sectors in a bank's loan portfolio exceeding the 75^{th} percentile of the corresponding bank-(military) sector shares' distribution	DealScan & Authors' calculations	0/1
Relative specialization in conflict country	Either the ratio of the average bank-(conflict) country share to the average (conflict) country-world share (Paravisini et al., 2023) or the difference between the two (Blickle et al., 2024) exceeding the 75^{th} percentile of the corresponding 'ratio' or 'difference' distribution	DealScan & Authors' calculations	0/1
Relative specialization in military sector	Either the ratio of the average bank-(military) sector share to the average (military) sector-world share (Paravisini et al., 2023) or the difference between the two (Blickle et al., 2024) exceeding the 75^{th} percentile of the corresponding 'ratio' or 'difference' distribution	DealScan & Authors' calculations	0/1
NATO	*Dummy* = 1 if a country belongs to NATO	www.nato.int	0/1
G7	*Dummy* = 1 if a country belongs to G7	Wikipedia	0/1
BRICS	*Dummy* = 1 if a country belongs to BRICS	Wikipedia	0/1
UN West	Countries that vote similar to the US in the UN General Assembly (bottom quartile of the difference of ideal points)	Bailey et al. (2017) & Authors' calculations	0/1
UN East	Countries that vote oppositely to the US in the UN General Assembly (top quartile of the difference of ideal points)	Bailey et al. (2017) & Authors' calculations	0/1
UN Neutral	Countries whose voting patterns in the UN General Assembly fall between alignment with the US and alignment with China/Eastern bloc (middle two quartiles of the difference of ideal points)	Bailey et al. (2017) & Authors' calculations	0/1
Post-conflict	Dummy = 1 for the year(s) after a conflict and where deaths were lower than 1,000 deaths	UCDP & Authors' calculations	0/1
Capital distance	Distance between the capital of the bank country and capital of the firm country	CEPII GeoDist	log km
Primary Industries	*Dummy* = 1 if the loan is to a firm with SIC codes 0100 - 1,499	DealScan,	0/1
Industry & Manufact.	*Dummy* = 1 if the loan is to a firm with SIC codes 1,500 - 3,999	NAICS/SIC website	0/1
Utilities & Infrastructure	*Dummy* = 1 if the loan is to a firm with SIC codes 4,000 - 4,999	& Authors' calculations	0/1
Wholesale	*Dummy* = 1 if the loan is to a firm with SIC codes 5,000 - 5,199		0/1
Retail	*Dummy* = 1 if the loan is to a firm with SIC codes 5,200 - 5,999		0/1
Services	*Dummy* = 1 if the loan is to a firm with SIC codes 6,000 - 8,999		0/1

C.1 Descriptive statistics

Table C.II. Descriptive statistics

	N	Mean	SD	Min	25th	Median	75th	Max
Main variables								
Loan amount (log)	1,324,617	16.48	2.43	9.16	15.86	17.09	18.02	20.64
Foreign	1,324,617	0.46	0.50	0	0	0	1	1
Military (primary & dual)	1,324,617	0.17	0.38	0	0	0	0	1
Military (primary)	1,324,617	0.003	0.06	0	0	0	0	1
Military (dual)	1,324,617	0.17	0.06	0	0	0	0	1
Deaths	1,324,617	36.38	216.64	0	0	0	0	10,211
Conflict dummy (500)	1,324,617	0.02	0.15	0	0	0	0	1
Conflict dummy (1,000)	1,324,617	0.01	0.10	0	0	0	0	1
Home-Country blocs								
NATO	1,324,617	0.66	0.47	0	0	1	1	1
G7	1,324,617	0.74	0.44	0	0	1	1	1
BRICS	1,324,617	0.05	0.21	0	0	0	0	1
UN West	1,324,617	0.82	0.38	0	1	1	1	1
UN East	1,324,617	0.03	0.17	0	0	0	0	1
UN Neutral	1,324,617	0.11	0.31	0	0	0	0	1
Bank specialization								
Bank-(conflict) country relative (RS_{bc}, Paravisini et al., 2023)	1,324,617	0.19	0.39	0	0	0	0	1
Bank-(military) sector relative (RS_{bs}, Paravisini et al., 2023)	1,324,617	0.22	0.41	0	0	0	0	1
Others								
Post-war	1,324,617	0.01	0.01	0	0	0	0	1
Capital distance	1,323,023	3.81	4.16	0	0	0	8.68	9.90
Sectors								
Primary Industries	1,324,617	0.08	0.27	0	0	0	0	1
Industry & Manufacturing	1,324,617	0.24	0.42	0	0	0	0	1
Utilities & Infrastructure	1,324,617	0.15	0.35	0	0	0	0	1
Wholesale	1,324,617	0.04	0.20	0	0	0	0	1
Retail	1,324,617	0.06	0.24	0	0	0	0	1
Services	1,324,617	0.34	0.47	0	0	0	1	1

Note: This table shows descriptive statistics for all variables used in the empirical analyses. For the variable definitions, refer to Table C.I. The sample period is 1989-2020. Data sourced from UCDP, DealScan, Bailey et al. (2017), NAICS/SIC webiste, and CEPII GeoDist.

Appendix D Primary and dual-use military sectors

Table D.I. Four-digit industry classification of military-related sectors

Panel A: Primary military-related sectors	
SIC Code	Description
2892	Explosives
3482	Small Arms Ammunition
3483	Ammunition, Except for Small Arms
3484	Small Arms
3489	Ordnance and Accessories, Not Elsewhere Classified
3761	Guided Missiles and Space Vehicles
3764	Guided Missile and Space Vehicle Propulsion Units and Propulsion Unit Parts
3769	Guided Missile Space Vehicles Parts and Auxiliary Equipment, Not Elsewhere Classified
3795	Tanks and Tank Components
9711	National Security

Panel B: Dual-use sectors	
SIC Code	Description
Category 0 - Nuclear materials, facilities, and equipment	
2819	Industrial Inorganic Chemicals, Not Elsewhere Classified
2869	Industrial Organic Chemicals, Not Elsewhere Classified
3443	Fabricated Plate Work (Boiler Shops)
3462	Iron and Steel Forgings
3491	Industrial Valves
3559	Special Industry Machinery, Not Elsewhere Classified
3823	Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products
3829	Measuring and Controlling Devices, Not Elsewhere Classified
3844	X-Ray Apparatus and Tubes and Related Irradiation Apparatus
3845	Electromedical and Electrotherapeutic Apparatus
Category 1 - Special materials and related equipment	
2836	Biological Products, Except Diagnostic Substances
3312	Steel Works, Blast Furnaces (Including Coke Ovens), and Rolling Mills
3499	Fabricated Metal Products, Not Elsewhere Classified
Category 2 - Materials processing	
2899	Chemicals and Chemical Preparations, Not Elsewhere Classified
3541	Machine Tools, Metal Cutting Types
3542	Machine Tools, Metal Forming Types
3544	Special Dies and Tools, Die Sets, Jigs and Fixtures, and Industrial Molds
3549	Metalworking Machinery, Not Elsewhere Classified
3567	Industrial Process Furnaces and Ovens
3821	Laboratory Apparatus and Furniture
3823	Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products
3829	Measuring and Controlling Devices, Not Elsewhere Classified
Category 3 - Electronics	
3469	Metal Stampings, Not Elsewhere Classified
3571	Electronic Computers
3612	Power, Distribution, and Specialty Transformers
3629	Electrical Industrial Apparatus, Not Elsewhere Classified
3669	Communications Equipment, Not Elsewhere Classified
3674	Semiconductors and Related Devices
3675	Electronic Capacitors

3676 Electronic Resistors
3677 Electronic Coils, Transformers, and Other Inductors
3678 Electronic Connectors
3679 Electronic Components, Not Elsewhere Classified
3699 Electrical Machinery, Equipment, and Supplies, Not Elsewhere
3824 Totalizing Fluid Meters and Counting Devices
3825 Instruments for Measuring and Testing of Electricity and Electrical Signals
3861 Photographic Equipment and Supplies
5063 Electrical Apparatus and Equipment Wiring Supplies, and Construction Materials
5065 Electronic Parts and Equipment, Not Elsewhere Classified

Category 4 - Computers

3572 Computer Storage Devices
3575 Computer Terminals
3577 Computer Peripheral Equipment, Not Elsewhere Classified
3695 Magnetic And Optical Recording Media
7371 Computer Programming Services
7372 Prepackaged Software
7373 Computer Integrated Systems Design
7374 Computer Processing and Data Preparation and Processing Services
7376 Computer Facilities Management Services
7379 Computer Related Services, Not Elsewhere Classified

Category 5 - Telecommunications and "information security"

3357 Drawing and Insulating of Nonferrous Wire
3661 Telephone and Telegraph Apparatus
3663 Radio and Television Broadcasting and Communications Equipment
3669 Communications Equipment, Not Elsewhere Classified
4812 Radiotelephone Communications
4813 Telephone Communications, Except Radiotelephone
4822 Telegraph and Other Message Communications
4899 Communications Services, Not Elsewhere Classified

Category 6 - Sensors and lasers

3699 Electrical Machinery, Equipment, and Supplies, Not Elsewhere
3822 Automatic Controls for Regulating Residential and Commercial Environments and Appliances
3826 Laboratory Analytical Instruments

Category 7 - Navigation and avionics

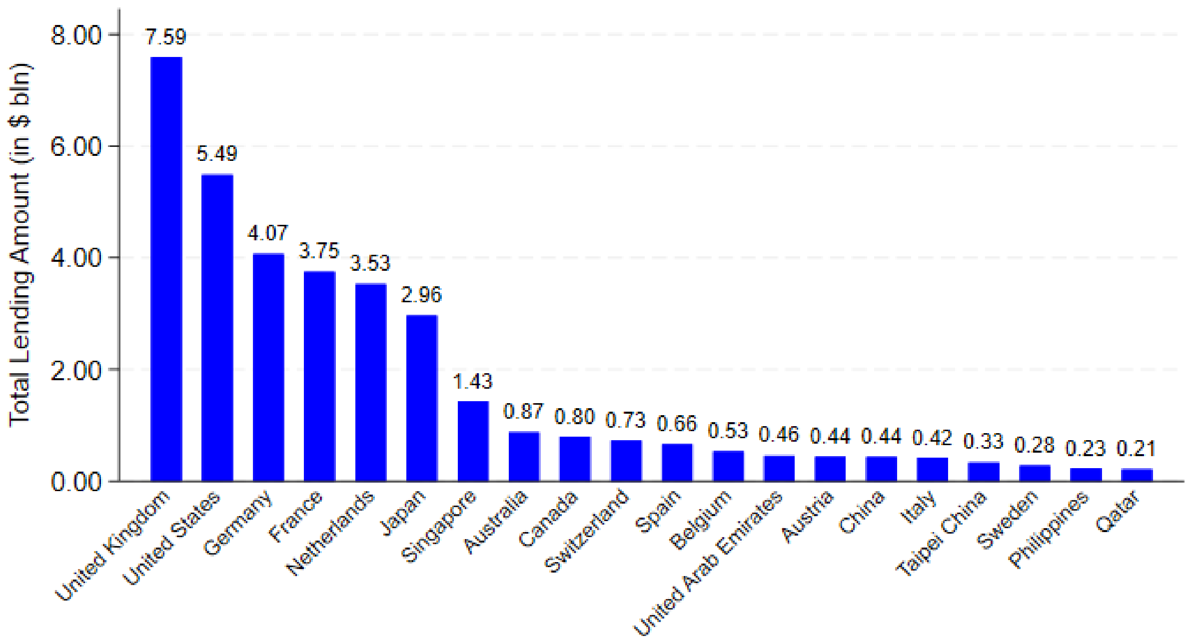
3357 Drawing and Insulating of Nonferrous Wire
3369 Nonferrous Foundries, Except Aluminum and Copper
3463 Nonferrous Forgings
3492 Fluid Power Valves and Hose Fittings
3511 Steam, Gas, and Hydraulic Turbines, and Turbine Generator Set Units
3519 Internal Combustion Engines, Not Elsewhere Classified
3536 Overhead Traveling Cranes, Hoists, and Monorail Systems
3566 Speed Changers, Industrial High-Speed Drives, and Gears
3594 Fluid Power Pumps and Motors
3621 Motors and Generators
3694 Electrical Equipment for Internal Combustion Engines
3721 Aircraft
3724 Aircraft Engines and Engine Parts
3728 Aircraft Parts and Auxiliary Equipment, Not Elsewhere Classified
3812 Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems and Instruments
3824 Totalizing Fluid Meters and Counting Devices
3829 Measuring and Controlling Devices, Not Elsewhere Classified
4581 Airports, Flying Fields, and Airport Terminal Services

5088	Transportation Equipment and Supplies, Except Motor Vehicles
Category 8 - Marine	
3519	Internal Combustion Engines, Not Elsewhere Classified
3561	Pumps and Pumping Equipment
3625	Relays and Industrial Controls
3731	Ship Building and Repairing
3732	Boat Building and Repairing
3823	Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products
5088	Transportation Equipment and Supplies, Except Motor Vehicles
8711	Engineering Services
Category 9 - Aerospace and propulsion	
3643	Current-Carrying Wiring Devices
3829	Measuring and Controlling Devices, Not Elsewhere Classified
5088	Transportation Equipment and Supplies, Except Motor Vehicles
9661	Space Research and Technology

Note: We refer to the UK Military List and the UK Dual-Use List from the UK Strategic Export Control List provided by the UK Department for Business and Trade for military-related (e.g., "explosives," "weapons," "defense") and dual-use (e.g. "telecommunications", "electronics") terms and hand-collect 4-digit SIC codes searching for those terms on the NAICS website. Panel A shows the 10 primary military SIC Codes while Panel B lists the 79 unique dual-use SIC Codes having a minimum 50% likelihood of being of military purpose.

Appendix E Syndicated credit to military sectors: Main source countries

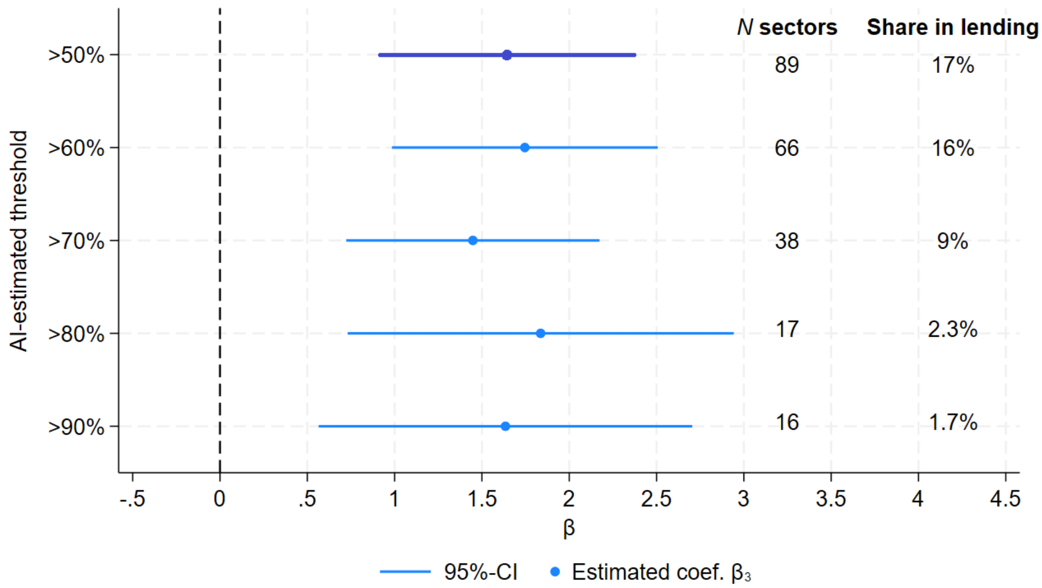
Figure E.I. Top-20 countries in terms of lending amount to militaries during violent conflict



Note: This figure shows top-20 home countries in terms of the absolute amount (in $) of military-related lending to conflict countries during a violent conflict (1989–2020). Violent conflict is defined as a situation in which a country experiences more than 1,000 battle-field related deaths in a calendar year. Data sources: Uppsala Conflict Data Program and DealScan.

Appendix F Robustness to AI thresholds for dual-use sectors

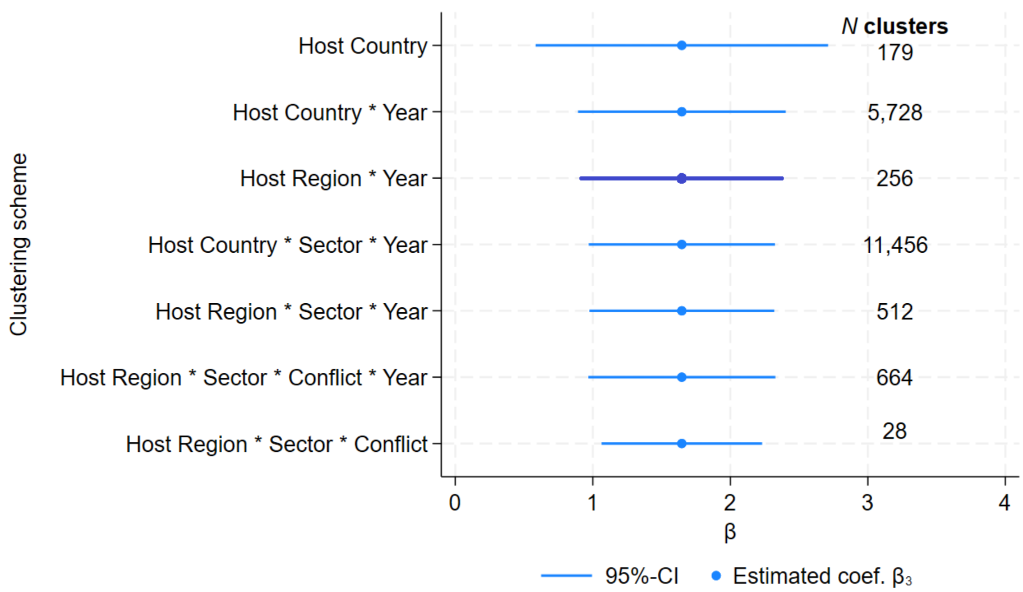
Figure F.I. Cross-border lending to firms in military sectors during violent conflicts: Estimates at the aggregate level using different subsets of dual-use sectors



Note: The figure reports the estimates of the β_3 coefficient on the $Conflict \times Foreign \times Military$ variable, as implied by Equation (1), with the corresponding 95% confidence intervals, which are based on standard error's clustering by home country. $Foreign$ is a dummy equal to one (zero) when indicating aggregate cross-border (domestic) lending to a country. $Conflict$ is a dummy variable equal to one if the country that received syndicated loans experienced more than 1,000 battle-field related deaths in a calendar year. $Military$ is a dummy equal to one if the loan is to a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). In the figure, each estimate grounds on a particular AI-classification of dual-use SIC codes that we retrieve from the UK Strategic Export Control List, as described in Appendix B. Specifically, we make a request to AI to assign probabilities of being used for the military purposes to each dual-use SIC code from the List, starting from 50% (baseline), with the step of 10 pp. The resultant number of SIC-codes for each AI-based probability threshold is reported in *N sectors* and the unconditional share of loans received by the firms operating in these SIC codes in the total syndicated lending in the full sample across all times is reported in *Share in lending*. The 50% threshold is used as the baseline (marked in dark blue). The data is sourced from the Uppsala Conflict Data Program and DealScan.

Appendix G Robustness to different clustering schemes

Figure G.I. Cross-border lending to firms in military sectors during violent conflicts: Estimates at the aggregate level using different clustering of standard errors



Note: The figure reports the baseline estimate of the β_3 coefficient on the $Conflict \times Foreign \times Military$ variable, as implied by Equation (1) and reported in Table 1, and the corresponding 95% confidence intervals that are based on different schemes of standard error's clustering. $Foreign$ is a dummy equal to one (zero) when indicating aggregate cross-border (domestic) lending to a country. $Conflict$ is a dummy variable equal to one if the country that received syndicated loans experienced more than 1,000 battle-field related deaths in a calendar year. $Military$ is a dummy equal to one if the loan is to a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). In the figure, *Host* (*Home*) *Country* (*Region*) means the country (region) where the credit comes from (arrives in). Region contains 7 regions: East Asia and Pacific; North America; Europe and Central Asia; Latin America and the Caribbean; Middle East and North Africa; South Asia; Sub-Saharan Africa). The host-country clustering scheme is used as the baseline (marked in dark blue). The data is sourced from the Uppsala Conflict Data Program and DealScan.

Appendix H Robustness to inverse hyperbolic sine transformation of the dependent variable

Table H.I. Cross-Border Lending to Military Firms During Violent Conflicts: Aggregate-Level Analysis in Logs

		Dependent variable: $IHS(Loan_{gsct})$		
		(1)	(2)	(3)
Foreign	β_0	0.403***	0.436***	
		(0.018)	(0.020)	
Foreign × Conflict	β_1	0.016	-0.129**	-0.115**
		(0.058)	(0.056)	(0.056)
Foreign × Military	β_2		-0.091***	
			(0.017)	
Foreign × Conflict × Military	β_3		0.465***	0.464***
			(0.144)	(0.144)
Conflict		✓	✓	✓
Host Country × Year FE		✓	✓	✓
Conflict × Military FE			✓	✓
Foreign × Military FE				✓
Military × Year FE				✓
Foreign × Year FE				✓
N obs		22,652	22,652	22,652
N of host region × year clusters		229	229	229
R^2 (adj.)		0.188	0.223	0.225
Linear test: $\beta_1 + \beta_3 = 0$			*0.336***	*0.349***
			(0.140)	*(0.139)*

Note: This table shows the results from estimating Equation (1) using the Poisson Pseudo-Maximum Likelihood approach with high-dimensional fixed effects (Correia et al., 2020). The dependent variable is the inverse hyperbolic sine (*IHS*) transformation of total loans y by bank group g to sector s in country c and year t, where IHS is computed as $\ln(y+\sqrt{y^2+1})$. The dependent variable is winsorized at the 99.5 percentile to reduce potential contamination from outliers in the right tail. $Foreign_{gc}$ is a dummy equal to one (zero) when indicating aggregate cross-border (domestic) lending to country c. *Conflict* is a dummy variable equal to one if the country in which the firm is domiciled, experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). All regressions include fixed effects as specified. *Foreign Region FE* capture the following source regions of foreign credit: East Asia and Pacific; North America, Latin America, and the Caribbean; Middle East and North Africa; South Asia; and Sub-Saharan Africa. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the destination country level and reported in parentheses.

Appendix I Robustness to the regression in shares

Table I.I. Cross-Border Lending to Military Firms During Violent Conflicts: Aggregate-Level Analysis in Shares

Dependent variable:	$Military\, Loans_{gct}$, % of $Total\, Loans_{ct}$			
	(1)	(2)	(3)	(4)
Foreign	1.482***	1.466***		
	(0.057)	(0.057)		
Foreign × Conflict		1.048**	1.014*	0.956*
		(0.533)	(0.530)	(0.573)
Conflict	✓	✓	✓	✓
Host Region × Year FE		✓	✓	✓
Foreign × Year FE			✓	✓
Foreign × Host Country FE				✓
N obs	10,596	10,596	10,596	6,503
N of Home Country × Year clusters	211	211	211	211
R^2 (adj.)	0.105	0.105	0.106	0.166

Note: This table shows the results from estimating Equation (1) using the Poisson Pseudo-Maximum Likelihood approach with high-dimensional fixed effects (Correia et al., 2020). The dependent variable is the share of military-related loans by bank group g in country c and year t in the total loans in that country in that year. The dependent variable is winsorized at the 99.5 percentile to reduce potential contamination from outliers in the right tail. $Foreign_{gc}$ is a dummy equal to one (zero) when indicating aggregate cross-border (domestic) lending to country c. *Conflict* is a dummy variable equal to one if the country in which the firm is domiciled, experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). All regressions include fixed effects as specified. *Foreign Region FE* capture the following source regions of foreign credit: East Asia and Pacific; North America, Latin America, and the Caribbean; Middle East and North Africa; South Asia; and Sub-Saharan Africa. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the destination country level and reported in parentheses.

Appendix J Other measures of violent conflict

Table J.I. Cross-border lending during violent conflicts: Different indicator thresholds

	Dependent variable: $Loan_{bft}$					
$\mathbb{1}_{\{deaths \geq j\}}$	$j = 0$	$j = 100$	$j = 250$	$j = 500$	$j = 750$	$j = 1,000$
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict × Foreign	0.024	0.098	0.132	0.028	-0.259**	-0.310***
	(0.026)	(0.075)	(0.142)	(0.134)	(0.103)	(0.115)
Conflict × Military × Foreign	0.070**	0.113***	0.418***	0.554***	0.424***	0.521***
	(0.027)	(0.040)	(0.092)	(0.092)	(0.094)	(0.105)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓	✓	✓
N obs	1,308,048	1,308,048	1,308,048	1,308,048	1,308,048	1,308,048
N of banks	14,021	14,021	14,021	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2). The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector which is either primary or dual (see Table D.I for the relevant SIC codes). We vary the *Conflict* dummy with different death thresholds and make it equal to one if the country, in which the firm is domiciled, experienced more than 100, 250, 500, 750, and 1,000 battle-field related deaths in a calendar year, respectively. Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

Table J.II. Cross-border lending during violent conflicts: Different continuous thresholds

	Dependent variable: $Loan_{bft}$					
	Conflict: *deaths*, conditional on *deaths* $\geq j$:					
	$j = 0$	$j = 100$	$j = 250$	$j = 500$	$j = 750$	$j = 1,000$
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.000	0.014	0.015	0.000	-0.037***	-0.042***
	(0.000)	(0.013)	(0.021)	(0.019)	(0.014)	(0.015)
Foreign × Conflict × Military	0.000***	0.023***	0.065***	0.080***	0.059***	0.067***
	(0.000)	(0.007)	(0.013)	(0.013)	(0.013)	(0.015)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓	✓	✓
N obs	1,308,048	1,308,048	1,308,048	1,308,048	1,308,048	1,308,048
N of banks	14,021	14,021	14,021	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2). The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Military* is a dummy variable equal to one if the loan is extended to a firm operating in military-related SIC sectors (see Table D.I for the relevant SIC codes). In all columns, we use deaths as a continuous threshold to measure the intensity of the *Conflict*. Threshold j represents a point where values below j are coded as zero, while values above j maintain their continuity. Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

Appendix K Decomposition of military sectors

Table K.I. Primary vs. dual-use military sectors

	Dependent variable: $Loan_{bft}$		
	Primary & Dual-use	Dual-use only	Primary-use only
	(1)	(2)	(3)
Conflict × Foreign	-0.310***	-0.304***	-0.219*
	(0.115)	(0.114)	(0.116)
Conflict × Military × Foreign	0.521***	0.483***	0.486**
	(0.105)	(0.105)	(0.210)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Conflict × Military FE	✓	✓	✓
Foreign × Military FE	✓	✓	✓
Military × Year FE	✓	✓	✓
Foreign × Year FE	✓	✓	✓
N obs	1,308,048	1,308,048	1,308,048
N of banks	14,021	14,021	14,021
R^2 (adj.)	0.868	0.868	0.868

Note: This table shows the results from estimating Equation (2). The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. In column (1), *Military* is a dummy equal to one if the loan is extended to a firm operating in both primary and dual-use military-related SIC sectors which are either primary or dual (see Table D.I for the relevant SIC codes). In column (2), *Military* is a dummy equal to one if the loan is extended to a firm operating in dual-use SIC sectors only. In column (3), *Military* is a dummy equal to one if the loan is extended to a firm operating in primary military-related SIC sectors only. Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

Appendix L Robustness: Loan composition and definition

Table L.I. Robustness: Loan composition and syndicate structure

Dependent variable	$Loan_{bft}$					
	Baseline	Equal shares	Lead≤5	Lead≤10	Loan type	Loan purpose
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.310***	-0.145**	-0.384***	-0.283**	-0.333***	-0.312***
	(0.115)	(0.069)	(0.122)	(0.115)	(0.114)	(0.117)
Foreign × Conflict × Military	0.521***	0.346***	0.312***	0.307***	0.311***	0.365***
	(0.105)	(0.075)	(0.107)	(0.093)	(0.100)	(0.092)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓	✓	✓
N obs	1,308,048	1,307,028	1,176,846	1,266,805	900,315	1,201,878
N of banks	14,021	14,013	13,718	13,957	10,909	13,638
R^2 (adj.)	0.868	0.886	0.872	0.869	0.894	0.877

Note: The table shows the results from estimating Equation (2) after imputing the missing loan shares in different ways. The dependent variable is the natural logarithm of the loan amount. Column (1) shows our baseline specification. In column (2), we split the loan amount equally among all banks in the syndicate. In columns (3) and (4), we exclude facilities with more than 5 and 10 lead banks, respectively. Column (5) keeps only common loan types, i.e., Revolver/line ≥ 1 year and Term Loans. Column (6) finally removes takeovers and acquisition lines. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector (see Table D.I for the relevant SIC codes). Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

Appendix M Excluding major source countries

Table M.I. Cross-border lending during violent conflicts:
Excluding foreign banks from major economies

Dependent variable	$Loan_{bft}$					
Excl. banks from	US	Japan	DE	FR	China	UK
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.316***	-0.301***	-0.302***	-0.312***	-0.319***	-0.335***
	(0.117)	(0.116)	(0.115)	(0.117)	(0.116)	(0.119)
Foreign × Conflict × Military	0.551***	0.529***	0.492***	0.518***	0.540***	0.373***
	(0.112)	(0.107)	(0.110)	(0.108)	(0.108)	(0.089)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓	✓	✓
N obs	872,880	1,104,600	1,224,094	1,227,106	1,271,769	1,229,756
N of banks	9,399	12,681	13,361	13,459	13,106	13,574
R^2 (adj.)	0.890	0.765	0.872	0.871	0.869	0.872

Note: The table shows the results after excluding major economies in our dataset. We exclude banks from the US, Japan, Germany, France, and China in column 1, 2, 3, 4, and 5, respectively. The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector (see Table D.I for the relevant SIC codes). Fixed effects as specified. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank in parentheses.

Appendix N Robustness to using only largest lenders

Table N.I. Loan-level regressions: Keep only largest lenders

Dependent variable	$Loan_{bfsct}$		
	(1)	(2)	(3)
Foreign	-0.101***	-0.104***	
	(0.011)	(0.011)	
Foreign × Conflict	-0.449**	-0.539***	-0.525***
	(0.190)	(0.187)	(0.188)
Foreign × Military		0.013	
		(0.009)	
Foreign × Conflict × Military		0.405**	0.410**
		(0.159)	(0.159)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Conflict × Military FE		✓	✓
Foreign × Military FE			✓
Military × Year FE			✓
Foreign × Year FE			✓
N obs	980,396	980,396	980,396
N of banks	575	575	575
R^2 (adj.)	0.879	0.879	0.879

Note: This table shows the results from estimating Equation (2) when the sample is drastically reduced to the 575 largest global syndicated lenders. The dependent variable is the natural logarithm of the loan amount. *Foreign* is a dummy equal to one if the bank lends to a firm in a foreign country. *Conflict* is a dummy equal to one if the firm's country experienced more than 1,000 battle-field related deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military-related SIC sector (see Table D.I for the relevant SIC codes). All regressions include fixed effects as specified. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank are shown in parentheses.

Appendix O Composition of country dyads

Table O.I. West-to-West, West-to-Neutral, and West-to-East country dyads, 1989–2020

West home	West (conflict) host	West home	Neutral (conflict) host	West home	East (conflict) host
Albania	Israel	Andorra	Angola	Australia	Algeria
Australia	Russia	Australia	Colombia	Austria	Colombia
Austria	Türkiye	Austria	India	Belgium	Congo, DR
Belgium	Ukraine	Belgium	Iraq	Canada	India
Bulgaria		Bermuda	Nigeria	Czech Republic	Iraq
Canada		Canada	Pakistan	Finland	Liberia
Croatia		Croatia	Philippines	France	Nigeria
Czech Republic		Czech Republic	Russia	Germany	Pakistan
Denmark		Denmark	Sri Lanka	Italy	Philippines
Finland		Finland	Türkiye	Japan	Sri Lanka
France		France		Netherlands	
Germany		Germany		Norway	
Greece		Greece		Portugal	
Ireland		Hungary		Spain	
Israel		Iceland		Sweden	
Italy		Ireland		Switzerland	
Japan		Israel		Taipei China	
Malta		Italy		United Kingdom	
Netherlands		Japan		United States	
Norway		Latvia			
Poland		Liechtenstein			
Portugal		Luxembourg			
Slovakia		Netherlands			
South Korea		Norway			
Spain		Poland			
Sweden		Portugal			
Switzerland		Russia			
Taipei China		Slovakia			
United Kingdom		Slovenia			
United States		South Korea			
		Spain			
		Sweden			
		Switzerland			
		Taipei China			
		United Kingdom			
		United States			
30	4	36	10	19	10

Table O.II. Neutral-to-West, Neutral-to-Neutral, and Neutral-to-East country dyads, 1989–2020

Neutral home	West (conflict) host	Neutral home	Neutral (conflict) host	Neutral home	East (conflict) host
Angola	Israel	Angola	Angola	Australia	Algeria
Austria	Russia	Argentina	Colombia	Austria	Colombia
Bahrain	Türkiye	Australia	India	Brazil	Congo, DR
China	Ukraine	Austria	Iraq	China	India
India		Azerbaijan	Nigeria	Ghana	Iraq
Japan		Bahrain	Pakistan	India	Liberia
Jordan		Bangladesh	Philippines	Ireland	Nigeria
Kuwait		Brazil	Russia	Ivory Coast	Pakistan
Mauritius		Chile	Sri Lanka	Japan	Philippines
Pakistan		China	Turkey	Kuwait	Sri Lanka
Qatar		Ghana		Lebanon	
Russia		India		Philippines	
Saudi Arabia		Ireland		Singapore	
Singapore		Ivory Coast		South Africa	
South Africa		Japan		South Korea	
South Korea		Jordan		Togo	
UAE		Kazakhstan		UAE	
		Kuwait			
		Malaysia			
		Mauritius			
		Mongolia			
		Morocco			
		Nigeria			
		Pakistan			
		Panama			
		Philippines			
		Qatar			
		Russia			
		Saudi Arabia			
		Singapore			
		South Africa			
		South Korea			
		Spain			
		Sri Lanka			
		Thailand			
		Togo			
		Tunisia			
		Türkiye			
		UAE			
		Venezuela			
17	4	40	10	17	10

Table O.III. East-to-West, East-to-Neutral, and East-to-East country dyads, 1989–2020

East home	West (conflict) host	East home	Neutral (conflict) host	East home	East (conflict) host
China	Israel	Bahrain	Angola	Afghanistan	Algeria
Egypt	Russia	Brunei	Colombia	Bahrain	Colombia
India	Türkiye	China	India	Brunei	Congo, DR
Indonesia	Ukraine	Egypt	Iraq	China	India
Lebanon		Hong Kong	Nigeria	Egypt	Iraq
Oman		India	Pakistan	Hong Kong	Liberia
Palestine		Indonesia	Philippines	India	Nigeria
Tunisia		Iran	Russia	Indonesia	Pakistan
		Jordan	Sri Lanka	Jordan	Philippines
		Kuwait	Türkiye	Kuwait	Sri Lanka
		Lebanon		Lebanon	
		Macau		Oman	
		Malaysia		Pakistan	
		Morocco		Philippines	
		Oman		Qatar	
		Pakistan		Thailand	
		Palestine		UAE	
		Philippines		Venezuela	
		Qatar			
		Saudi Arabia			
		Sri Lanka			
		Thailand			
		Tunisia			
		UAE			
8	4	24	10	18	10