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VIOLENT CONFLICT AND CROSS-BORDER LENDING

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Abstract

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JEL Classification: D74, F34, G15, G21, H56

Keywords: Cross-border lending

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December 23, 2025

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Keywords: Cross-border lending, syndicated loans, violent conflict, defense financing

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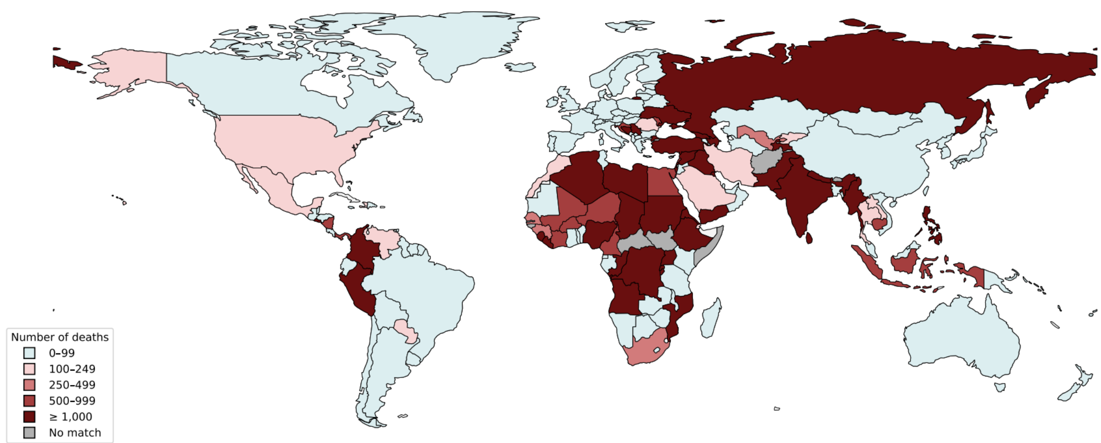
1 Introduction

Russia's war on Ukraine, escalating hostilities in the Middle East, and civil wars in Myanmar, Sudan, and Yemen have thrust armed conflict into sharp focus, prompting – alongside shifting US security commitments – a fundamental reassessment of global defense funding. NATO allies have committed to higher defense budgets, yet expanding military production requires more than government spending: private lenders provided $1 trillion to the global defense industry during 2020–2022 alone (Longo, Meggiolaro and Felipe, 2024). Although economists have examined how states use public debt to finance military endeavors (Kremer and Jayachandran, 2006; Reinhart and Rogoff, 2009; Zielinski, 2016), little is known about how private lenders respond to violent conflict. We shed light on this question through the lens of cross-border syndicated lending to defense-related firms.

Informed by Morgan, Rime and Strahan (2004)'s framework of bank capital reallocation, two countervailing hypotheses guide our empirical analysis. On the one hand, cross-border lenders typically retrench when faced with negative shocks to local economies – a well-documented "flight home" effect (Giannetti and Laeven, 2012; De Haas and Van Horen, 2013). Violent conflict may amplify this tendency by damaging corporate assets and diminishing firms' ability to pledge collateral (Kirshner, 2007; Shpak, Earle, Gehlbach and Panga, 2023). This literature suggests that cross-border lending should decline relative to domestic lending during conflicts. Conversely, armed conflict may increase demand for credit in defense sectors. Cross-border lenders, less directly impacted by local hostilities and with access to deeper capital markets, may be well-positioned to accommodate this demand. Domestic banks, by contrast, often face immediate conflict-related constraints (such as physical damage to banking infrastructure and liquidity pressures from deposit withdrawals) that may limit their ability to expand military-sector lending.

To evaluate these countervailing mechanisms empirically, we leverage comprehensive syndicated loan data from DealScan, covering 1.3 million loans by 14,021 lenders to 97,169 firms across 179 countries between 1989 and 2020. Cross-border credit is a key component of global capital flows, with almost three-quarters coming in the form of syndicated loans (Doerr and Schaz, 2021). We merge these data with information from the Uppsala Conflict Data Program (UCDP), which provides measures of armed conflict, 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, 44 countries experienced at least one year with more than 500 battlefield deaths, and 38 countries saw at least one year exceeding 1,000 battlefield deaths.

Figure 1. Conflict countries by annual battlefield deaths



Note: This figure shows countries where annual battle-field related deaths exceeded a certain threshold at least once during 1989-2020. No match indicates no overlap between the Uppsala Conflict Data Program records and Dealscan. The nature and timing of each conflict is described in Appendix Table A.I. Data sources: Uppsala Conflict Data Program and DealScan.

Next, we identify military-related borrowers by distinguishing primary military sectors (exclusively producing defense goods) and dual-use sectors (civilian goods with military applications). Using 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. This approach identifies 10 primary military and 79 dual-use sectors with at least 50% average military-use probability, together representing 17% of our syndicated lending sample.

Drawing on this newly assembled dataset, we begin with an aggregate-level analysis comparing lending patterns by cross-border lenders versus domestic banks to military and non-military sectors during conflicts. We document two main results. First, cross-border lenders reduce overall credit to conflict countries relative to domestic banks – consistent with a flight-home effect. Second, during conflict episodes, cross-border lenders *increase* their lending to military and dual-use sectors. Taken together, violent conflicts trigger both an aggregate contraction in credit provision and a pronounced reallocation of cross-border lending from non-military to defense-related sectors. This dual pattern is also evident 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: cross-border lenders reduce credit 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 separately identify supply- and demand-side forces. The results reveal two distinct patterns. First, the overall retrenchment of cross-border lenders from conflict countries remains robust even after holding demand constant, consistent with a classic flight-home effect. Second, the increase in military lending stems primarily from heightened demand by defense firms that foreign banks are better positioned to accommodate, rather than supply-side targeting. To substantiate this interpretation, we estimate local projections following Jordà (2005) using the universe of firms in the Compustat database. We show that, during conflicts, military firms indeed experience disproportionately stronger revenue and profitability growth relative to civilian firms.

Next, we examine the real effects of cross-border lending on military versus civilian firms. We merge the Dealscan and Compustat datasets and estimate instrumental-variables (2SLS) regressions to trace how pre-conflict exposure to cross-border lenders affects firm outcomes through leverage changes during conflicts. In the first stage, greater pre-conflict exposure significantly reduces leverage among civilian firms while increasing leverage among military firms. In the second stage, these predicted leverage changes produce a relative expansion in military firms' tangible assets, revenues, and employment. Complementary reduced-form regressions yield qualitatively and quantitatively similar results. Overall, pre-conflict connections to cross-border lenders generate sharply divergent real effects on military versus civilian firms during violent conflicts.

We extend our baseline analysis in two main directions. First, following Kempf, Luo, Schäfer and Tsoutsoura (2023), who document political partisanship in cross-border lending during peacetime, we examine how banks adjust their lending in line with their home countries' 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. Two findings emerge. Banks from all regions increase military lending during conflicts. However, 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, increase military lending to Eastern and neutral conflict countries but not to Western conflict zones. The effect also strengthens with geographical distance: banks located farther from conflict zones increase defense-sector lending more. These patterns suggest that profit motives dominate when lending to politically distant countries, while political constraints or regulatory scrutiny may limit military financing within geopolitical blocs.

The second main extension examines how bank specialization shapes cross-border lending during violent conflicts, using measures of relative specialization (Paravisini, Rappoport and Schnabl, 2023; Blickle, Parlatore and Saunders, 2024). We document a generalized flight-home effect, with all banks reducing non-military lending to conflict zones. However, this retreat is offset by increased military lending from two distinct bank types. First, banks without prior country specialization redirect capital toward military sectors in conflict zones. Second, banks with established military sector expertise also sharply increase defense lending to conflict countries. These patterns indicate that reallocation is driven primarily by cross-border lenders with military expertise but limited country-specific relationships, which can meet heightened credit demand without jeopardizing established client ties.

Additional extensions delineate the boundaries of our main results. We find no 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 within three years after conflicts end, suggesting banks react to immediate dynamics rather than engage in long-term repositioning. Lastly, both state-owned and private banks, as well as bank and non-bank lenders, display similar reallocation patterns.

Related literature. We contribute to three main strands of the literature. First, we extend research on cross-border credit flows. Prior research documents a consistent flight-home effect: cross-border lenders retrench more sharply than domestic banks following adverse local shocks, transmitting financial and real-economic disruptions across borders.[1] Our analysis reveals a more nuanced pattern during violent conflicts: while cross-border lenders reduce overall lending (consistent with the flight-home effect), they simultaneously redirect capital toward military-related sectors positioned to benefit from local conflict. We show that these military lending increases stem primarily from heightened defense-sector demand that foreign banks are better positioned to accommodate. Meanwhile, the aggregate lending contraction persists after controlling for demand, consistent with supply-driven retrenchment.

Second, we contribute to the literature on financial markets and military conflict. Prior

[1]Prior studies document cross-border transmission of financial crises (Chava and Purnanandam, 2011; Cetorelli and Goldberg, 2011, 2012; Giannetti and Laeven, 2012; Popov and Udell, 2012; Schnabl, 2012; De Haas and Van Horen, 2012, 2013; Paravisini, Rappoport, Schnabl and Wolfenzon, 2015; Doerr and Schaz, 2021), shocks to risky assets (Popov and Van Horen, 2015; Altavilla, Pagano and Simonelli, 2017; Acharya, Eisert, Eufinger and Hirsch, 2018), regulatory changes (Aiyar, Calomiris, Hooley, Korniyenko and Wieladek, 2014; Tripathy, 2020; Borchert, De Haas, Kirschenmann and Schultz, 2026), and trade disruptions (Alfaro, Brussevich, Minoiu and Presbitero, 2025).

work focuses on sovereign borrowing: Horn, Reinhart and Trebesch (2024) show that wars are financed primarily by allies, with official government-to-government lending expanding while private investors withdraw. We show that this aggregate private withdrawal masks substantial reallocation. Cross-border lenders reduce civilian lending but increase military-sector credit relative to domestic banks – a channel invisible in aggregate analyses. This reallocation generates real effects: military firms with pre-conflict foreign bank relationships expand investment, revenues, and employment during conflicts, while similarly connected civilian firms contract. Our evidence thus points to a dual-track structure of war finance: sovereigns draw on official allied credit (DiGiuseppe, 2015; Horn et al., 2024), while private capital flows selectively to profitable defense industries, particularly when domestic credit markets are constrained (Mamonov, Ongena and Pestova, 2024).[2]

Third, we shed light on the financial dimensions of geopolitical fragmentation. Recent work documents how trade, investment, and supply chains have fragmented along geopolitical lines amid rising US-China tensions and Russia's invasion of Ukraine (Alfaro and Chor, 2023; Gopinath, Gourinchas, Presbitero and Topalova, 2025).[3] An emerging literature traces similar patterns in financial markets. Niepmann and Shen (2025) show that internationally active U.S. banks respond to heightened geopolitical risk by reducing cross-border lending while maintaining credit through local affiliates. This asymmetric adjustment spills over to domestic lending, generating significant real effects. Avril, McQuade, Pancaro and Reghezza (2025) document similar patterns for euro area banks. Related work on sanctions demonstrates that regulatory gaps allow banks to circumvent restrictions: German banks reduced direct lending to sanctioned countries while expanding credit through less-regulated foreign affiliates (Besedeš, Goldbach and Nitsch, 2017; Efing, Goldbach and Nitsch, 2023).

[2]Related work examines the macro- and microeconomic effects of war. At the macro level, studies consider how military spending and economic capacity shape war outcomes (Kennedy, 1987; Barro and Lee, 1994; Abadie and Gardeazabal, 2003; Glick and Taylor, 2010; Benmelech and Monteiro, 2025; Federle, Rohner and Schularick, 2025). At the micro level, research documents how households, banks, and firms respond to violent conflicts (Verwimp, Justino and Brück, 2019; Mishra, Ongena and Peng, 2025).

[3]See also Chupilkin, Javorcik and Plekhanov (2023), Aiyar, Malacrino and Presbitero (2024), and Chupilkin, Javorcik, Peeva and Plekhanov (2024) on connector countries and trade rerouting.

We examine violent conflicts as distinct shocks that trigger asymmetric reallocation rather than uniform retreat or regulatory arbitrage. Cross-border lenders reduce civilian lending while increasing military-sector financing, and this pattern concentrates in politically non-aligned countries. The literature on ideological determinants of cross-border capital allocation shows that, in peacetime, political ideology and alignment with foreign governments influence institutional investors' cross-border capital allocation (Kempf et al., 2023). Our findings reveal that violent conflicts can alter this dynamic: banks preferentially direct military financing toward non-aligned or distant countries while avoiding such lending within their own geopolitical blocs. This suggests that political constraints that bind during peacetime relax when profit opportunities arise in distant conflict zones.

2 Conceptual framework

We draw on Morgan et al. (2004)'s framework for capital allocation by integrated financial intermediaries, which extends Holmström and Tirole (1997) to multi-market settings. Integrated banks allocate capital toward locations offering the highest risk-adjusted returns. Financial integration thus cushions location-specific supply shocks but amplifies demand or collateral shocks by facilitating capital reallocation across markets.

Financial integration and credit reallocation. To fix ideas, consider two countries indexed by $j \in \{H, F\}$, where H denotes the home country of the lender and F denotes the foreign country of the borrower, which may be affected by violent conflict. Let A_j denote the aggregate collateral or pledgeable income of firms in country j, which determines the maximum expected return that borrowers can credibly promise to lenders. In the vein of Morgan et al. (2004), the return to bank capital deployed in country j can be represented as

$$\beta_j = g(A_j, K_j), \tag{1}$$

where K_j is the stock of bank capital competing for loans in that market. The return β_j is increasing in firm collateral A_j (more pledgeable income supports higher returns to monitoring) and decreasing in bank capital K_j, as lender competition compresses margins.

Under financial segmentation, bank capital is immobile and β_H and β_F are determined independently. Under financial integration, however, bank capital flows across borders to equalize risk-adjusted returns:

$$\beta_H = \beta_F = \beta^*. \tag{2}$$

This arbitrage condition is the source of the model's key predictions. When a shock reduces the return to lending in one country, integrated banks reallocate capital toward the other market until returns equalize at a new equilibrium.

Violent conflicts: Location-specific return shocks. Violent conflict constitutes a severe negative shock to the expected return on lending in the borrower country. Conflict raises macroeconomic uncertainty, weakens contract enforcement, destroys physical collateral, and increases the probability of expropriation. In Morgan et al. (2004), this corresponds to a negative collateral shock in country F: the pledgeable income that firms can credibly promise to lenders declines, reducing the return to bank capital deployed abroad.

Formally, let conflict reduce aggregate collateral in country F by $\Delta > 0$:

$$A_F \to A_F - \Delta. \tag{3}$$

This shock lowers β_F below β_H, creating a return differential that induces capital reallocation from the foreign market back toward the lender's home country. Bank capital exits F until the arbitrage condition is restored at a lower equilibrium return $\beta^{*\prime} < \beta^*$. The resulting contraction in K_F reduces credit supply in the conflict country, amplifying the initial collateral shock. This mechanism generates a flight-home effect: internationally active lenders reduce their foreign exposure and reallocate capital toward domestic uses.

The military sector and industry-specific return shocks. While conflict depresses returns to lending for most firms in the affected country, it simultaneously generates a positive shock to expected returns in military and dual-use sectors. To capture this, we extend the framework to allow for sector-specific variation in expected returns. For civilian firms, conflict destroys collateral and weakens contract enforcement, reducing pledgeable income in the standard sense. For military firms, government procurement contracts and wartime demand raise expected profitability, effectively increasing the share of returns that can be credibly pledged to lenders even absent improvements in physical collateral.

Let $s \in \{c, m\}$ index civilian and military sectors, respectively, with sectoral pledgeable income A_j^s. Conflict affects collateral asymmetrically across sectors in the foreign country:

$$\frac{\partial A_F^c}{\partial \mathit{Conflict}} < 0 \quad \text{and} \quad \frac{\partial A_F^m}{\partial \mathit{Conflict}} > 0. \tag{4}$$

The first inequality captures the destruction of civilian collateral values; the second reflects the enhanced profitability and implicit government support enjoyed by military-related firms during wartime. These opposing forces generate within-country heterogeneity in returns:

$$\beta_F^m > \beta^* > \beta_F^c. \tag{5}$$

Internationally integrated lenders are well positioned to exploit such sectoral return differentials. Because they can reallocate capital not only across countries but also across sectors, they shift lending toward activities whose returns are insulated or benefit from conflict. In a stylized equilibrium with free capital mobility across all country–sector pairs, the share of bank capital $\bar{K}$ allocated to country j and sector s is proportional to the collateral share. To illustrate the direction of reallocation, consider a stylized proportional allocation rule:

$$K_j^s = \frac{A_j^s}{\sum_{j',s'} A_{j'}^{s'}} \cdot \bar{K}. \tag{6}$$

This expression makes explicit that capital follows collateral. When conflict raises A_F^m while reducing A_F^c, integrated banks reallocate lending toward military-related firms in the conflict country in proportion to the relative increase in sectoral collateral values.

As a result, the framework implies a distinctive lending pattern during conflict. Aggregate lending to the conflict-affected country declines, while lending to military-related firms expands relative to civilian firms. This reallocation should be particularly pronounced for cross-border lenders, who can draw on diversified balance sheets and internal capital markets. By contrast, domestic lenders in the conflict country are more likely to face balance-sheet constraints and local disruptions, limiting their ability to reallocate credit across sectors.

Testable predictions. These mechanisms yield two testable predictions. First, cross-border lending to firms in conflict-affected foreign countries declines relative to domestic lending, with the contraction concentrated among civilian borrowers. Second, cross-border lending to military-related firms in conflict-affected countries increases during conflict. The aggregate effect of conflict on cross-border lending is ambiguous and depends on the sectoral composition of the borrower economy: the flight-home effect dominates for civilian firms, while the military lending channel dominates for defense-related firms.

3 Data

3.1 Data sources

Our analysis relies on two primary data sources. The first is the Uppsala Conflict Data Program (UCDP). The UCDP provides comprehensive and harmonized information on armed conflicts and organized violence since the 1970s. 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.

The second dataset is Loan Pricing Corporation's DealScan, which provides comprehensive global coverage of syndicated corporate lending over a 32-year period (1989-2020). The data allow us to observe syndicated loan transactions and lending relationships between financial institutions and borrowers across countries, sectors, and time. Our unit of observation is a bank–borrower loan share in a given year, constructed by splitting each loan into syndicate member shares. DealScan reports loan share allocations for 26% of loans; for the remainder, we impute shares using each bank's historical average share from loans with observed allocations and re-scale shares to sum to 100%.[4] All loan amounts are converted to U.S. dollars and dated to the year of origination. DealScan provides lender and borrower country information, which we supplement by manually verifying bank headquarters locations. Following the literature (Mian, 2006; Giannetti and Laeven, 2012), we classify a loan as foreign if the lending bank or its parent is incorporated in a different country than the borrower; for example, a loan from Citibank to a Nigerian firm is classified as foreign regardless of whether it is extended by Citibank US or a Citibank affiliate in Nigeria.[5]

3.2 Identifying military and dual-use sectors

A key element of our analysis is the distinction between lending to firms in military and non-military sectors. We classify military-related sectors into two categories: primary military and dual-use. Primary military sectors produce goods exclusively for defense purposes, such as missiles and tanks. Dual-use sectors, by contrast, produce civilian goods or technologies with clear military applications; for example, commercial aircraft engine technologies can be readily adapted for fighter jets, relying on similar materials, propulsion systems, and engineering principles.

In the absence of an established classification separating non-military, primary military, and dual-use sectors, we construct our own. We begin with the observation that many

[4] Results are robust to alternative imputation methods, including equal splits across syndicate members (De Haas and Van Horen, 2013). See Appendix Table G.VII.

[5] Results are robust to restricting the sample to loans provided by banks' headquarters. See Appendix Table G.IX.

countries maintain lists of items requiring export authorization, as the export of military-related products may raise national security concerns. 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 mention these goods. This yields 10 primary military SIC codes.

For the dual-use list, we apply a slightly modified version of the same approach. We extract keywords from UK dual-use category titles (e.g., nuclear, aircraft) and search for these terms in NAICS and SIC classifications, yielding 115 candidate dual-use SIC codes. We then assess each sector's likelihood of military association by asking ChatGPT-4o to estimate the probability of military production involvement for all 125 codes (10 primary military and 115 dual-use). We repeat this exercise 50 times with random SIC code orderings and compute average probabilities for each sector (see Appendix B). Figure B.I shows very high rank-order consistency across iterations, and ChatGPT-4o consistently assigns 95–100% probability to all primary military sectors. We retain the 10 primary military sectors and 79 dual-use sectors with an average probability of at least 50%, which together account for about 17% of total syndicated lending volume.[6]

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 is a syndicated loan arranged in 2015 by a consortium of 15 African, American, Chinese, and European banks to INT Towers

[6]Appendix Table E.I, Panels A and B, list the SIC codes for the primary military and dual-use sectors, respectively, based on the UK Military and Dual-Use Lists. 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.

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.

3.3 Descriptive statistics

Our sample spans the period 1989–2020 and contains 1,324,617 observations at the bank-firm-year level, reflecting 861,437 distinct bank-firm relationships, 14,021 unique creditors, and 97,169 unique borrowers.[7] Appendix Table C.I contains variable definitions while Appendix Table D.I presents summary statistics. The dependent variable is log loan amount at the bank-firm-year level (mean: 16.48, or $59.8 million). Foreign (cross-border) loans, in which banks lend money to firms in a different country from the one where the parent bank is domiciled, comprise 47% of all loans. Loans to dual-use sectors represent 16.8% of our sample, while another 0.3% are for primary military applications. The mean distance between bank and firm headquarters is 3,810 km.

All conflicts with over 1,000 annual battle-related deaths in our sample are intrastate, though 21% also involve interstate hostilities. About 2% of loans (30,252) go to firms in countries with 500+ deaths per year, and 1% (14,344) to countries exceeding 1,000 deaths. Appendix Figure F.I shows the top source countries for syndicated loans to military and dual-use sectors in conflict zones. The United Kingdom, United States, and Germany lead, but the list also includes Singapore, China, and the United Arab Emirates.

[7] 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.

4 Empirical strategy

4.1 Aggregate-level analysis

We first examine aggregate cross-border lending to military and civilian sectors during violent conflicts. Our goal is twofold: to explore whether these effects are economically significant 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-country-sector-year level, where 'bank group' distinguishes foreign banks (i.e., cross-border lenders) from domestic banks, 'country' denotes the borrower's location, and 'sector' identifies military versus non-military firms. We include zeros for country-year pairs without lending, creating a balanced panel that captures both intensive and extensive margins of cross-border lending during conflicts. We then specify the following regression equation:

$$\begin{aligned} Loan_{gsct} = {} & \beta_0 \cdot Foreign_{gc} \\ & + \beta_1 \cdot Foreign_{gc} \times Conflict_{ct} \\ & + \beta_2 \cdot Foreign_{gc} \times Military_s \\ & + \beta_3 \cdot Foreign_{gc} \times Conflict_{ct} \times Military_s \\ & + \alpha_{rt} + \gamma_{vs} + \delta_{gs} + \chi_{st} + \phi_{gt} + \theta_{gc} + \varepsilon_{gsct} \end{aligned} \tag{7}$$

where $Loan_{gsct}$ is the total loan amount (in USD) 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 aggregation yields a dependent variable with numerous zero observations, we employ the Poisson Pseudo Maximum Likelihood (PPML) estimator by Correia, Guimaraes and Zylkin (2020). $Foreign_{gc}$ is a dummy variable equal to one (zero) for cross-border (domestic) lending to country c. $Conflict_{ct}$ is a dummy variable equal to one if country c experiences a violent conflict in year t. Finally, $Military_s$ is a dummy variable equal to one if lending is to firms in the military sector.

By construction, β_1 captures changes in aggregate credit by foreign banks, relative to domestic banks, to non-military firms in countries experiencing violent conflicts, relative to non-conflict times. In contrast, β_3, our main coefficient of interest, captures the additional change in military-sector lending by foreign banks during conflicts, beyond their general conflict response and baseline military lending patterns. Finally, β_2 reflects differential lending by foreign banks to military sectors, relative to domestic banks, during non-conflict periods.

The specification includes the following high-dimensional fixed effects. First, α_{rt} are host region $\times$ year fixed effects that absorb all time-varying shocks common to destination countries within a region.[8] Second, γ_{vs} are violent conflict $\times$ sector fixed effects that absorb sectoral lending differences during conflicts common to both bank groups. Third, δ_{gs} are bank group $\times$ sector fixed effects that remove baseline differences between foreign and domestic banks in their propensity to lend to military sectors. Fourth, χ_{st} are sector $\times$ year fixed effects that capture time-varying aggregate shocks to military versus non-military sectors common to both bank groups. Fifth, ϕ_{gt} are bank group $\times$ year fixed effects absorbing aggregate time trends in foreign versus domestic lending. Finally, θ_{gc} are bank group $\times$ host country fixed effects capturing potential specialization of cross-border lenders in 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, creditors, or home countries of foreign banks. We therefore view this specification as suggestive but useful for gauging whether effects are economically meaningful in the aggregate.

Consistent with Section 2, two hypotheses emerge. First, cross-border lenders reduce lending more than domestic banks in response to adverse country shocks. Violent conflicts should therefore trigger a flight-home effect: $\beta_1 < 0$. Second, armed conflicts may increase credit demand in military sectors that domestic banks struggle to meet. Cross-border lenders

[8] Regions: *ECA* (Europe and Central Asia); *EAP* (East Asia and Pacific); *NA* (North America); *LAC* (Latin America and the Caribbean); *MENA* (Middle East and North Africa); *SAR* (South Asia); *SSA* (Sub-Saharan Africa); and all other countries. Appendix Appendix G discusses more granular host country $\times$ year fixed effects. Standard errors are clustered by region $\times$ year; Appendix Figure G.II shows robustness to alternative clustering.

fill this gap, increasing military lending relative to domestic banks ($\beta_3 > 0$).

4.2 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:

$$\begin{aligned} Loan_{bfsct} = {} & \beta_0 \cdot Foreign_{bf} \\ & + \beta_1 \cdot Foreign_{bf} \times Conflict_{ct} \\ & + \beta_2 \cdot Foreign_{bf} \times Military_s \\ & + \beta_3 \cdot Foreign_{bf} \times Conflict_{ct} \times Military_s \\ & + \alpha_b + \theta_f + \mu_{ht} + \nu_{ct} + \delta_{vs} + \chi_{gs} + \phi_{gt} + \tau_{st} + \varepsilon_{bfsct} \end{aligned} \tag{8}$$

where $Loan_{bfsct}$ denotes total loans by bank b to firm f in sector s in country c (the firm's country of incorporation) in year t. In this case, $Foreign_{bf}$ is a dummy equal to one if the creditor and borrower are domiciled in different countries. $Conflict_{ct}$ is a dummy equal to one if country c experienced a violent conflict in year t. $Military_s$ is a dummy equal to one if firm f's primary, secondary, or tertiary SIC code is part of the sector list in Table E.I.

β_1 captures changes in credit by cross-border lenders, relative to domestic banks, to non-military firms during violent conflicts, relative to non-conflict times. β_2 reflects differential lending by cross-border lenders to military firms in peacetime. β_3 captures the additional change in military-sector lending by cross-border lenders during conflicts – that is, whether foreign banks reallocate credit toward (or away from) military sectors during conflicts more than domestic banks do.

Bank fixed effects α_b control for time-invariant bank characteristics (risk appetite, capital constraints, business models) affecting credit allocation. Firm fixed effects θ_f absorb time-invariant differences in credit demand and creditworthiness. These fixed effects ensure that loan volume variations reflect actual changes over time rather than persistent differences between banks and firms.

We also include several interactive fixed effects. Bank incorporation ('home') country h $\times$ year t fixed effects (μ_{ht}) and firm incorporation ('host') country $\times$ year t fixed effects (ν_{ct}) absorb shocks common to all banks or firms, respectively, in their country of incorporation at the same point in time. Violent conflict v $\times$ sector s fixed effects (δ_{vs}) absorb sectoral lending differences during conflicts that are common to domestic and cross-border lenders. Bank group g $\times$ 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. Bank group g $\times$ year t fixed effects (ϕ_{gt}) net out aggregate time trends in cross-border versus domestic lending. Finally, sector s $\times$ year t fixed effects (τ_{st}) account for time-varying aggregate shocks to the military sector that are common to both foreign and domestic lenders.

Our prior hypotheses extend to the loan-level analysis. Consistent with literature on cross-border lending during crises, foreign lenders may reduce credit more strongly in response to adverse local shocks ($\beta_1 < 0$). Conversely, violent conflicts may increase military firms' credit demand. Cross-border lenders, with greater spare capacity and deeper internal capital markets, may be better positioned to meet this demand ($\beta_3 > 0$).

5 Main results

5.1 Aggregate results

Table 1 presents estimates from Equation (7) using a balanced panel of 179 countries over 32 years, distinguishing foreign versus domestic bank groups and military versus non-military sectors. This yields 22,912 country $\times$ year $\times$ bank group $\times$ sector observations. The sample drops to 22,652 in columns (1)-(2) and 20,354 in columns (3)-(4) as high-dimensional fixed effects cause the PPML estimator to drop separated observations (Correia et al., 2020). Bank group $\times$ sector fixed effects (δ_{gs}) and bank group $\times$ host country fixed effects (θ_{gc}) in columns (3)-(4) absorb the *Foreign* × *Military* interaction (β_2) as well as the *Foreign* main effect (β_0). The $Conflict_{ct}$ and $Military_s$ dummies are absorbed by conflict × sector fixed effects (γ_{vs}) in all specifications.

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	0.623***	0.647***		
		(0.035)	(0.033)		
Foreign × Conflict	β_1	0.335	0.168	-0.567*	-0.624**
		(0.353)	(0.363)	(0.324)	(0.316)
Foreign × Military	β_2		-0.096*		
			(0.050)		
Foreign × Conflict × Military	β_3		1.591***	1.591***	1.568***
			(0.389)	(0.389)	(0.386)
Conflict		✓	✓	✓	✓
Host Region × Year FE		✓	✓	✓	✓
Conflict × Military FE			✓	✓	✓
Foreign × Military FE				✓	✓
Foreign × Host Country FE				✓	✓
Military × Year FE					✓
Foreign × Year FE					✓
N obs		22,652	22,652	20,354	20,354
N of Host Region × Year clusters		229	229	229	229
R^2 (adj.)		0.377	0.428	0.822	0.825

Note: Poisson Pseudo-Maximum Likelihood estimates with high-dimensional fixed effects (Correia et al., 2020). Dependent variable is total loan amount (billions of USD) by bank group g to sector s in country c and year t, winsorized at the 99.5th percentile. *Foreign* equals one for cross-border lending. *Conflict* equals one if the borrower's country experienced >1,000 battlefield deaths in a calendar year. *Military* equals one for loans to military-related SIC sectors (Table E.I). Host regions: ECA (Europe and Central Asia), EAP (East Asia and Pacific), NA (North America), LAC (Latin America and Caribbean), MENA (Middle East and North Africa), SAR (South Asia), SSA (Sub-Saharan Africa), and Rest. Data: UCDP and DealScan. Standard errors clustered by host region × year. ***, **, * denote significance at 1%, 5%, and 10%.

In column (1), we include the indicator $Foreign$ and its interaction with $Conflict$, controlling for host region × year fixed effects and the level effect of $Conflict$. The results show that foreign lending generally exceeds domestic lending in non-conflict periods, highlighting the importance of cross-border syndicated lending. However, foreign and domestic lending respond similarly when a country experiences violent conflict. In column (2), we add the interaction between *Foreign* and *Military*, as well as the triple interaction $Foreign \times Conflict \times Military$. We find that foreign banks lend significantly less to military sectors than domestic banks on average. Importantly, the positive and highly significant estimate of β_3 indicates that this pattern reverses during conflicts, with cross-border lenders expanding lending to defense-related projects relative to domestic banks.

This contrasting pattern is confirmed in column (3), where we add $Foreign \times Military$ and $Foreign \times Host\ Country$ fixed effects. The estimate of β_1 becomes negative and statistically significant at the 10% level, indicating that, relative to domestic banks and to non-conflict periods, foreign banks reduce non-military lending during conflicts – consistent with the flight-home effect discussed in Section 2. Importantly, β_3 remains positive and significant at the 1% level. Moreover, while the inclusion of these high-dimensional fixed effects nearly doubles the model's fit, it has little effect on the magnitude of β_3.

Finally, in column (4) we add $Military \times Year$ and $Foreign \times Year$ fixed effects. The point estimate of β_1 is now significant at the 5% statistical level, strengthening the notion of a standard flight-home effect during crisis times. Importantly, we continue to obtain a positive and highly significant point estimate of β_3, which confirms that the general pattern does not hold for lending to military-related sectors. Compared to domestic banks, cross-border lenders expand their lending to military-related sectors during conflicts.

Numerically, the point estimates imply that relative to non-conflict times, lending by foreign banks to the non-military sector falls by $e^{-0.624} - 1$ during conflicts, or by 46.5 percent more than lending by domestic banks.[9] In contrast, lending by foreign banks to the military sector increases substantially by around $e^{-0.624+1.568} - 1$ during conflict times, or by around 157.2 percent more than lending by domestic banks (significant at the 1% level).

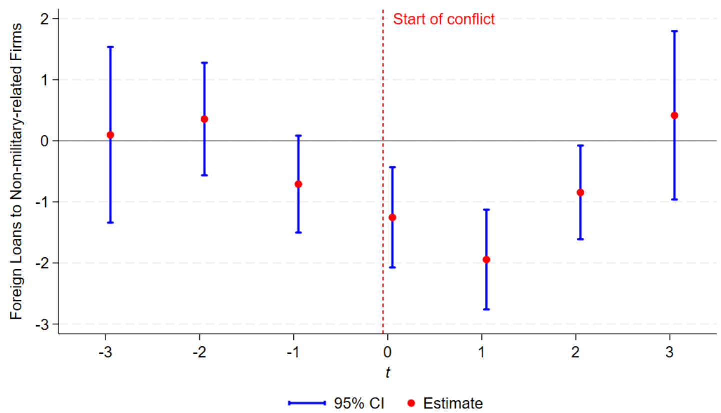
Figure 2 plots annual coefficients for β_1 (panel *a*) and β_3 (panel *b*) over a three-year

[9] 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.

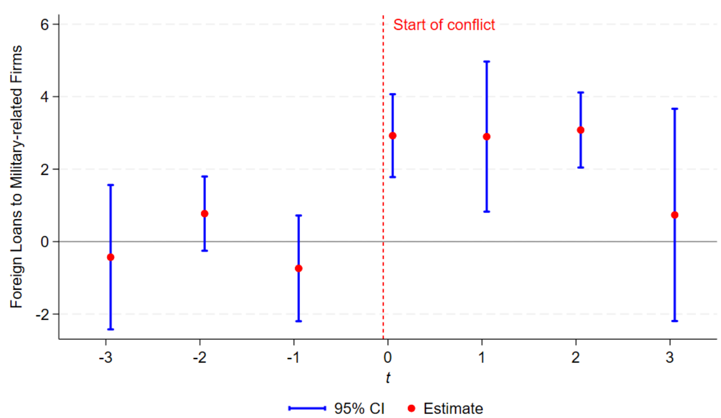
event window around conflict onset. The patterns support the identification strategy and the results in Table 1.

Figure 2. 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: Event study estimates of β_1 and β_3 from Table 1, column (4), replacing the *Conflict* dummy with year indicators spanning three years before and after conflict onset. Data: Uppsala Conflict Data Program and DealScan.

First, cross-border 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 cross-border 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.[10]

Robustness. We verify robustness through several tests (Appendix Appendix G). First, varying the dual-use sector threshold (50%-90%) yields robust results (Figure G.I). Second, coefficients remain significant across alternative clustering approaches (Figure G.II). Third, results hold when using an inverse hyperbolic sine transformation to address outliers (Table G.I). Fourth, our findings are robust to using military lending shares rather than levels (Table G.II). Finally, we use more granular $Host\,Country \times Year$ fixed effects in place of $Host\,Region \times Year$ fixed effects (Table G.III). While this absorbs most of the variation needed to identify the general flight-home effect, our key finding on military lending reallocation remains robust.

5.2 Loan-level results

Table 2 reports estimates from Equation (8). Following Table 1, we progressively add fixed effects, with column (3) including all interactive fixed effects from Section 4.2. In that column, bank group × sector fixed effects absorb the *Foreign* × *Military* interaction, while foreign × year fixed effects absorb the *Foreign* main effect. Consequently, β_0 and β_2 are identified only in columns (1)-(2). Similarly, $Conflict$, $Military$, $Foreign$, and $Conflict \times Military$ are absorbed by corresponding fixed effects in column (3).

In column (1), we only use bank and firm fixed effects as well as interactions of home-country and host-country dummies with year dummies. We find 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 $e^{-0.226} - 1$, or by about 20.2 percent. In

[10] The statistically insignificant decline in non-military lending at *t=-1* likely reflects our strict conflict definition (>1,000 battlefield deaths). Hostilities may commence in the prior year but register fewer casualties until crossing this threshold.

column (2), we add the double interaction of $Foreign$ and $Military$ and 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	-0.083***	-0.089***	
	(0.010)	(0.010)	
Foreign × Conflict	-0.226*	-0.322***	-0.313***
	(0.117)	(0.117)	(0.116)
Foreign × Military		0.027***	
		(0.008)	
Foreign × Conflict × Military		0.509***	0.523***
		(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.)	0.864	0.866	0.867

Note: This table reports estimates of Equation (8). The dependent variable is the log loan amount. *Foreign* equals one if a bank lends to a firm in another country; *Conflict* equals one if the borrower's country experiences >1,000 battlefield deaths in a year; and *Military* equals one if the borrower operates in a primary or dual-use military SIC sector (see Table E.I). All regressions include the fixed effects indicated. Data are from UCDP and DealScan. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors (in parentheses) clustered by bank.

We obtain very similar effects, both in terms of statistical significance and in terms of economic magnitude, once we add the interaction of the $Military$ and the $Foreign$ dummy as well as both dummies interacted with year dummies (column 3). In this preferred specification, we find that relative to domestic lending, cross-border lending to a firm in the non-military sector declines by $e^{-0.313} - 1$, or by about 26.9 percent, while cross-border lending to a firm in the military sector increases by $e^{(0.523-0.313)} - 1$, or by 23.4 percent, again relative to domestic banks. The explanatory power of the regression is quite high, at 87%.

Our headline results align with the conceptual framework outlined in Section 2. While foreign lending declines to conflict countries – consistent with the flight-home effect from negative location-specific shocks (Prediction 1) – this reduction applies only to non-military firms. In contrast, cross-border lending to military firms increases substantially, consistent with positive sector-specific return shocks during conflict (Prediction 2).

Robustness. We subject our loan-level results to extensive robustness checks (Appendix G). First, in Appendix Tables G.IV and G.V we vary the conflict intensity threshold from zero to 1,000 battlefield deaths, finding that both the flight-home effect and military lending reallocation strengthen with conflict severity. Second, in Appendix Table G.VI, we refine our military sector classification by separating primary military from dual-use sectors, and employ alternative classification methods including AI-based identification and sanctions-derived HS6-SIC mappings from Chupilkin et al. (2023), with consistent results throughout. Third, in Appendix Table G.VII, we address measurement concerns in syndicated lending by employing alternative loan share imputation methods, restricting the sample by lead arranger counts, and focusing on standard loan types. Our main findings continue to obtain. Fourth, in Appendix Table G.VIII, we confirm that our findings are not driven by major source countries, as the results continue to obtain when we exclude (one at a time) loans from the US, Japan, Germany, France, China, or the UK. Finally, in Appendix Table G.IX, we verify robustness across different lender samples, restricting analysis to the 575 largest global banks and excluding affiliate-based lending to isolate pure cross-border effects.

5.3 Credit supply versus credit demand

5.3.1 Analysis at the bank-firm level

Our evidence indicates that violent conflicts lead cross-border lenders to increase military-sector credit relative to domestic banks while reducing exposure to the rest of the economy. But are these effects supply-driven, demand-driven, or both?[11] We run tests in the spirit of Khwaja and Mian (2008) to help answer this question. The idea is to exploit two features of the syndicated loan market. First, banks lend to multiple firms within short periods; thus, bank × year fixed effects can hold bank-specific credit supply constant. Second, firms in the same country-sector receive multiple loans simultaneously; thus, host country × sector × year fixed effects can hold demand constant at the country-sector-year level.

Table 3 reports estimates from these versions of Equation (8). Column (1) presents our baseline results. In column (2), we saturate the model with bank × year fixed effects to hold credit supply constant, allowing us to isolate credit-demand effects. Conversely, column (3) includes host country × military sector × year fixed effects to control for shocks to country-sector credit demand, which helps us isolate credit-supply effects. Finally, columns (4)-(6) replicate columns (1)-(3), but also include bank × firm fixed effects to control for assortative matching between banks and firms and time-invariant relationship characteristics (Schwert, 2018; Chodorow-Reich, 2014).[12]

When controlling for supply factors (columns (2) and (5)), the increase in military-sector lending during conflicts persists, with the coefficient on the triple interaction remaining positive and significant. The economic magnitude is approximately 14% larger in column (2) compared to the baseline specification in column (1), and approximately 19% larger in column (5) compared to column (4) when accounting for bank-firm relationships. However, in both cases, the point estimate of β_1 is not statistically significant. Conversely, when we

[11] A straightforward approach would examine interest rate spreads on military versus non-military loans across conflict and non-conflict countries. Unfortunately, spread data are too incomplete: available for 38.3% of US loans but only 1.7% of non-US loans.

[12] Here, observations decline by about half as we lose bank–firm pairs observed only once.

Table 3. Credit supply, credit demand, and bank-firm relationships

Dependent variable	$Loan_{bfsct}$					
	Baseline	Demand	Supply	Baseline	Demand	Supply
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.313***	-0.248	-0.275**	-0.469*	-0.299	-0.397*
	(0.116)	(0.155)	(0.112)	(0.251)	(0.326)	(0.205)
Foreign × Conflict × Military	0.523***	0.595***	0.099	0.555**	0.659**	0.047
	(0.105)	(0.105)	(0.133)	(0.235)	(0.259)	(0.364)
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.)	0.867	0.872	0.868	0.894	0.898	0.896

Note: This table shows the results from estimating Equation (8) with additional fixed effects. 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 E.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.

control for time-varying country-sector demand in columns (3) and (6), the point estimate of β_3 becomes statistically insignificant, while that of β_1 remains negative and significant.

These patterns are more consistent with demand-driven reallocation toward military firms – arising from sector-specific demand shocks that cross-border lenders are better positioned to accommodate – than with proactive supply-side targeting. At the same time, foreign banks' broader retrenchment from conflict countries remains robust after controlling for demand, consistent with a supply-driven flight home.

5.3.2 Firm performance during violent conflicts

We now test whether military firms become relatively more attractive borrowers during violent conflicts, which which would be consistent with both heightened credit demand and greater willingness by cross-border lenders to meet it. Using Compustat data on 70,533 civilian and 13,439 military firms across 124 countries (1,068,807 observations), we track firm performance during conflict episodes. If military firms experience disproportionate increases in revenues and profitability relative to civilian firms during local conflicts, this would enhance their creditworthiness and reduce perceived default risk.

To implement local projections (Jordà, 2005) in a panel setting (Jordà and Taylor, 2016), we estimate the following regressions:

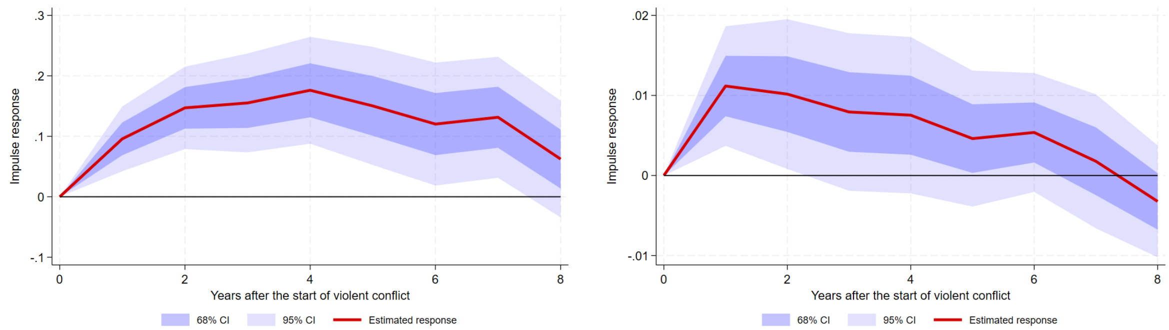
$$\ln y_{fsct+h} = \alpha_f + \lambda_{cs} + \theta_{ct} + \delta_{st} + \beta_h \cdot Conflict_{ct} \times Military_s + \varepsilon_{fsct+h} \tag{9}$$

where y_{fsct+h} measures firm performance at horizon h ($h = 1, 2...8$) following conflict onset in year t. We examine two performance measures: total revenues and EBIT as a percentage of total assets (winsorized at 97.5%). The sample spans firms f in 4-digit SIC sectors s across countries c during 1988-2020 (variable definitions and summary statistics in Appendix Tables C.I and D.I).

We include a rich set of fixed effects to absorb unobserved heterogeneity. First, firm fixed effects α_f control for time-invariant differences (size, managerial quality, etc.) that systematically affect firms' ability to generate revenues or sustain profitability. Second, country × sector fixed effects λ_{cs} capture structural differences in industrial specialization across countries that influence firms' long-run revenue potential. Third, country × year fixed effects θ_{ct} absorb shocks (e.g., business cycle fluctuations or fiscal disruptions) that affect firms' revenues and profitability in a specific country and year. Finally, sector × year fixed effects δ_{st} account for global shocks specific to industries (e.g., sector-specific technological innovations) that can directly influence sectoral earnings capacity and profit ratios.

In this setting, our baseline hypothesis is that due to rising demand for military products, the performance of military firms increases more than that of civilian firms during violent conflict ($\beta_h > 0$).

Figure 3. Firm performance during violent conflicts: Local projections



(a) Revenue (b) EBIT, % total assets

Note: The figure reports estimates of Equation (9) using firm-year data. The dependent variable is (a) log total revenue and (b) EBIT-to-assets. *Conflict* equals one if the firm's country experiences > 1,000 battlefield deaths in a year, and *Military* equals one if the firm operates in a primary or dual-use military SIC sector (see Table E.I). The number of observations ranges from 871,571 ($h = 1$) to 448,563 ($h = 8$) in panel (a), and from 914,539 ($h = 1$) to 473,120 ($h = 8$) in panel (b). Data are from UCDP and Compustat. Standard errors are clustered at the host country $\times$ year level.

Figure 3 reports estimates of Equation (9). We find positive and highly significant coefficients β_h for military firms' revenues (panel a) and pre-tax, pre-interest earnings (panel b), indicating that military firms grow faster and become more profitable than civilian firms during violent conflicts. These dynamics likely increase both their demand for credit and their attractiveness to (cross-border) lenders. Economically, military firms' revenues rise by 19.7% ($e^{0.18} - 1$) relative to civilian firms within four years of conflict onset. This effect gradually reverses over the following four years, indicating a persistent yet transitory impact on sales. In parallel, pre-tax, pre-interest earnings (as a percentage of total assets) increase by about 1.1 percentage points more than those of civilian firms in the first year of conflict.

5.4 The real effects of cross-border lending

Our loan-level results suggest that greater pre-conflict exposure to cross-border lenders may increase leverage for military firms during conflicts, while reducing leverage for civilian firms, potentially leading military firms to expand investment and employment relative to civilian firms. To test this mechanism, we adopt a two-stage framework that instruments firm leverage during conflicts with *pre-conflict* exposure to cross-border lending.[13] We hypothesize that greater pre-conflict exposure to cross-border lenders facilitates borrowing and growth for military firms during conflicts, while generating the opposite effects for civilian firms due to the contraction in civilian lending.

We construct a firm-level sample for conflict countries by merging Compustat with DealScan. Due to the limited overlap, we retain both matched firms and those appearing only in Compustat with positive pre-conflict long-term debt; for Compustat-only firms, we set pre-conflict syndicated borrowing to zero.[14] Finally, we define a firm's pre-conflict cross-border exposure as its share of cross-border loans in total borrowing during $[t^*-3, t^*-2]$:

$$Foreign\,Share_{fsct_c^*} = \frac{\sum_{\ell=2}^{3} Foreign\,Loan_{bft_c^*-\ell}}{\sum_{\ell=2}^{3} Total\,Loan_{bft_c^*-\ell}} \tag{10}$$

where t_c^* is the onset of conflict in country c.

[13]Using pre-conflict exposure mitigates endogeneity in bank–firm relationships (Petersen and Rajan, 1994; Sufi, 2009).

[14]To mitigate pre-trends (Figure 2a), we exclude the year $t^* - 1$ and require firms to be observed at least once in both the pre- and post-conflict periods within a symmetric three-year window. To address varying conflict durations, we collapse the panel into a cross-section by averaging outcomes over the first k conflict years ($k = 3$ in the baseline; robust for $k_{max} \in [4, 17]$).

We then specify the following 2SLS regression:

$$\textbf{1st stage: } Log(Debt_{fsct_c^*}) = \theta_{cst} + \varphi_1 \cdot Foreign\,Share_{fsct_c^*} + \varphi_2 \cdot Foreign\,Share_{fsct_c^*} \times Military_s + \gamma \cdot \mathbb{1}\{Borrowing\}_{fsct_c^*} + \epsilon_{fsct_c^*} \tag{11}$$

$$\textbf{2nd stage: } Log(Y_{fsct_c^*}) = \theta_{cst} + \beta \cdot Log(\widehat{Debt}_{fsct_c^*}) + \varepsilon_{fsct_c^*} \tag{12}$$

where the first-stage dependent variable, *Debt*, is total long-term debt averaged over the first three conflict years. Y_{fsct} represents the second-stage outcomes (tangible assets, revenues, or employment) averaged over the same period. The dummy $\mathbb{1}\{Borrowing\}_{fsct_c^*}$ identifies firms that borrowed from any bank during the pre-conflict window ($t^* - 3$ to $t^* - 2$). The first-stage coefficients, φ_1 and φ_2, measure how pre-conflict cross-border exposure drives changes in leverage for civilian and military firms, respectively. Both equations include country × sector × first-conflict-year fixed effects (θ_{cst}). These capture aggregate shocks affecting military and civilian firms differently within a conflict country and account for cross-country variation in military specialization.[15] Finally, we weight all regressions by inverse firm revenues. This reduces the influence of large, diversified corporations and emphasizes variation among smaller, credit-constrained firms, whose outcomes are more sensitive to credit supply shocks. Standard errors are clustered at the country × sector level.

Table 4 presents the 2SLS results. Our analysis of tangible assets and revenues includes 268 military and 2,903 civilian firms (up to 3,374 observations). Of these, 65 military and 328 civilian firms had pre-conflict cross-border borrowing exposure. The employment subsample is smaller, with 842 observations. The first-stage results (columns 1, 3, and 5) support our hypotheses. Pre-conflict cross-border exposure reduces debt for civilian firms (significant in the tangible assets and revenue samples) but significantly increases it for military firms. A

[15] While some countries in the Uppsala dataset experience only one conflict, others have up to four distinct conflict-start years between 1989 and 2020.

Table 4. Firm performance during violent conflicts: 2SLS estimates

Dependent variable	Debt	Tangible Assets	Debt	Revenue	Debt	Employment
	1st-stage	*2nd-stage*	*1st-stage*	*2nd-stage*	*1st-stage*	*2nd-stage*
	(1)	(2)	(3)	(4)	(5)	(6)
Borrowing (0/1)	4.412***		4.412***		4.634***	
	(0.533)		(0.533)		(1.109)	
Foreign share	-1.321*		-1.321*		−1.830	
	(0.793)		(0.793)		(1.233)	
Foreign share × Military	2.920**		2.920**		4.590***	
	(1.357)		(1.357)		(1.735)	
Debt (*predicted*)		1.282***		1.423***		0.613***
		(0.122)		(0.210)		(0.111)
Host Country × Military × Year FE	✓	✓	✓	✓	✓	✓
N obs	3,374	3,374	3,374	3,374	842	842
N conflicting countries	12	12	12	12	11	11
N of military firms	268	268	268	268	74	74
N of civilian firms	2,903	2,903	2,903	2,903	702	702
SD of Foreign share ($Military = 0$)	0.117		0.117		0.181	
SD of Foreign share ($Military = 1$)	0.169		0.169		0.245	
First-stage F-statistic	37.36		37.36		23.77	
P-value of Hansen's J-test		0.489		0.141		0.259

Note: This table presents 2SLS estimates from equations (11) and (12). The first-stage dependent variable is the log of total long-term debt (*Debt*, columns 1, 3, 5). Second-stage dependent variables are the logs of tangible assets (col. 2), total revenues (col. 4), and employment (col. 6), each averaged over the first three conflict years ($t \in [t^*, t^* + 3]$).$Borrowing\,(0/1)$ indicates borrowing from any bank during $t^* - 3$ or $t^* - 2$; we exclude $t^* - 1$ to mitigate pre-trends (Figure 2). $Foreign\,share$ measures pre-conflict exposure to cross-border lenders during $t^* - 3$ and $t^* - 2$ (Eq. 10); for Compustat firms without DealScan records, this share is set to zero. *Military* is a dummy for primary or dual-use military SIC sectors (Table E.I).All regressions include specified fixed effects and use inverse firm revenues as weights to emphasize variation among smaller, credit-constrained firms. First-stage F-statistics are Kleibergen-Paap rk Wald. Data are from UCDP, DealScan, and Compustat. Standard errors (in parentheses) are clustered by country × sector. ***, **, * denote significance at the 1

one-standard-deviation increase in $Foreign\,Share$ decreases civilian leverage by 14.2% while increasing military leverage by 31.2%. First-stage F-statistics confirm instrument strength.

The second-stage estimates in columns (2)-(4)-(6) show that predicted leverage ($\widehat{Debt}$) is a positive and highly significant determinant of firm-level outcomes. The results imply that the reallocation of syndicated credit toward military firms (and away from civilian ones) translates into divergent paths for corporate investment and growth. A one-standard-deviation higher pre-conflict share of cross-border lending implies, through its effect on leverage, substantial real contractions for civilian firms: tangible assets, revenues, and employment fall by 18.2%, 20.2%, and 17.3%, respectively. Conversely, military firms experience corresponding increases of 40.0%, 44.4%, and 59.3%. The results are robust to extending the pre-conflict window to $t^* - 4$ (Table H.I).

6 Extensions

This section extends our analysis in several directions. First, we investigate the influence of geopolitical alignment and bank specialization on lending patterns. Second, we examine the geographical prevalence and temporal persistence of these patterns.

6.1 Geopolitical alignment and cross-border lending

We first examine whether the reallocation of credit toward military firms is influenced by geopolitical considerations. Specifically, we investigate the role of geopolitical distance between a bank's home country and the conflict destination. While Western banks are typically viewed as profit-oriented, non-Western institutions (often state-owned) may prioritize national strategic interests. These institutional differences may result in a heterogeneous propensity to support foreign military firms during conflict.

We test this hypothesis by categorizing countries according to either formal bloc memberships or time-varying UN General Assembly voting patterns (Bailey, Strezhnev and Voeten, 2017). By replacing the *Foreign* indicator in Equation (8) with dummies for geopolitical orientation, we move beyond a simple domestic-foreign dichotomy. This empirical setup identifies whether lending shifts are driven by the creditor's origin or by the geopolitical proximity between the bank's headquarters and the destination country.

6.1.1 Creditor origin and credit reallocation

Table 5 distinguishes creditors by their home countries' geopolitical affiliations. We categorize countries using membership in formal alliances and informal forums as proxies for geopolitical orientation. We compare NATO (30 countries, excluding Montenegro due to data limitations and recent members Finland and Sweden) with BRICS (Brazil, Russia, India, China, and South Africa). The remaining 122 countries are classified as "Others".

Column (1) shows that banks across all three groups significantly increase military lending to conflict-affected countries. While the effect is numerically largest for the "Others" category and smallest for NATO members, it remains statistically significant at the 1% level for all groups. In column (2), we replace NATO with the G7 as an alternative proxy for Western-aligned economies.[16] Consistent with our previous findings, all foreign bank groups, regardless of geopolitical orientation, expand lending to military firms in conflict zones. This expansion is again most pronounced for banks in the "Others" category, with all coefficients significant at the 1% level.

Our second approach categorizes countries into Western, Eastern, or non-aligned blocs using UN General Assembly voting patterns rather than formal membership. Following Bailey et al. (2017), we use ideal point distances that quantify foreign policy alignment with the US-led liberal order. This measure tracks changes in state preferences over time, independent of the UN agenda. 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 "East UN", and those in the middle two quartiles as "Neutral".[17] This ensures that the blocs are mutually exclusive at any point in time while allowing countries to change their geopolitical stance over time.

Column (3) reports results using this time-varying UN voting classification. Cross-border

[16] Russia was a member of the G8 from 1997 until its expulsion in 2014.

[17] 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.

Table 5. 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	-0.290**	-0.298**	-0.139**
	(0.115)	(0.113)	(0.076)
Conflict × B_2 Foreign	-0.234**	-0.232**	-0.162***
	(0.112)	(0.114)	(0.076)
Conflict × B_3 Foreign	-0.265**	-0.243**	-0.103
	(0.111)	(0.110)	(0.083)
Conflict × Military × B_1 Foreign	0.510***	0.501***	0.331***
	(0.158)	(0.158)	(0.103)
Conflict × Military × B_2 Foreign	0.424***	0.427***	0.428***
	(0.109)	(0.107)	(0.132)
Conflict × Military × B_3 Foreign	0.644***	0.616***	0.444***
	(0.100)	(0.107)	(0.123)
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	0.867	0.868
N countries in bloc B_1	5	5	48
N countries in bloc B_2	29	7	45
N countries in bloc B_3	95	117	85

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 $>$ 1,000 battle-field deaths in a calendar year. *Military* is a dummy equal to one if the loan is to a firm in a military SIC sector which is either primary or dual (see Table E.I for the relevant SIC codes). In column (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 by a bank from a country leaning towards the West (East) bloc to a firm domiciled in a foreign country. All regressions include 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.

lenders from all blocs significantly expand military credit relative to domestic banks, but magnitudes vary substantially: "Neutral"-country banks increase military lending by 40.7 percent versus 21.2 percent for "West UN" banks, a nearly twofold difference.

6.1.2 Dyadic alignment and credit reallocation

We next examine whether dyadic geopolitical alignment between creditor and borrower countries influences the reallocation of credit toward military firms. 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 (8) by replacing $Foreign$ with dyadic dummies for different types of geopolitical alignment. We first classify both creditor and borrower countries into "UN West", "UN East", or "UN Neutral" groups using the same methodology as above, and then create nine dyadic combinations representing all possible creditor-borrower geopolitical alignments.[18]

Column (1) of Table 6 examines how banks from "UN West" countries reallocate credit based on the borrower's geopolitical alignment. We find that Western banks significantly increase military lending to Eastern and Neutral conflict zones – by 40.4% and 24.5%, respectively – but *reduce* lending to military firms in Western-aligned conflict countries by 57.4%. This suggests that while Western banks pursue profit opportunities in politically distant markets, they may face regulatory constraints, reputational risks, or policy pressures that discourage financing military activities in allied nations. Columns (2) and (3) reveal similar selective patterns for other blocs. Banks from neutral countries increase military lending only to other neutral destinations (34.2%), while "UN East" banks significantly expand lending only to neutral conflict zones (41.8%). Notably, neither neutral nor Eastern banks show significant military lending responses to Western-aligned conflict countries, and Eastern banks show no significant response within their own bloc.

Together, Tables 5 and 6 indicate that while military reallocation is global, its magnitude

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

Table 6. 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	-0.276***	0.137	-0.227
	(0.096)	(0.118)	(0.170)
Conflict × B_{i2} Foreign	-0.142**	-0.131	-0.166**
	(0.084)	(0.087)	(0.083)
Conflict × B_{i3} Foreign	-0.165	-0.113	-0.094
	(0.122)	(0.139)	(0.135)
Conflict × Military × B_{i1} Foreign	-0.577***	n/a	n/a
	(0.128)		
Conflict × Military × B_{i2} Foreign	0.361***	0.425***	0.515***
	(0.114)	(0.131)	(0.154)
Conflict × Military × B_{i3} Foreign	0.504**	0.310	-0.130
	(0.241)	(0.219)	(0.288)
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	1,308,048	1,308,048
N banks	14,021	14,021	14,021
R^2 (adj.)	0.867	0.867	0.867
N home/(conflict) host countries in dyad bloc B_{i1}	29/4	17/3	7/3
N home/(conflict) host countries in dyad bloc B_{i2}	32/10	40/11	20/11
N home/(conflict) host countries in dyad bloc B_{i3}	16/9	16/6	17/9

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 primary military or dual-use SIC sector (see Table E.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* denotes nine dummy variables ($i, j = 1, 2, 3$) equal to one if the loan is extended by a bank from country bloc i to a firm in country bloc j (when $i = j$, we additionally require bank and firm to be located in different countries). All results come from a single regression including the full set of nine dyadic interactions. Each column reports coefficients for banks from a specific origin bloc lending to each of the three destination blocs: column (1) shows coefficients for West-origin banks ($i = 1$); column (2) for Neutral-origin banks ($i = 2$); and column (3) for East-origin banks ($i = 3$). All regressions include fixed effects as specified. "*n/a*" means no syndicated loan deals on the market between specific geopolitical blocs. Data sources: UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank are shown in parentheses.

depends on dyadic alignment. All bank groups increase military lending to neutral countries, yet none expand such lending to Western-aligned conflict zones. These patterns suggest a "strategic distance" mechanism: conflicts create conditions where profit motives dominate out-group lending. For Western banks, in-group military financing appears constrained by allied coordination or regulatory oversight – they significantly reduce military lending to Western-aligned conflict countries. Eastern banks show no significant in-group response, while neutral banks, lacking comparable alliance structures, increase military lending even to other neutral destinations.

6.2 Bank specialization and cross-border conflict lending

A recent literature documents large differences in lending specialization across banks (Paravisini et al., 2023; Blickle et al., 2024; Alfaro et al., 2025) and finds that these specialization patterns influence banks' lending decisions, especially in times of instability. Our results may therefore partially reflect the tendency of some banks to tilt their lending permanently 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 two 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 firms f in all foreign countries or sectors, respectively:

$$CS_{bct} = \frac{\sum_{f} Loan_{bfct}}{\sum_{c}\sum_{f} Loan_{bfct}}, \qquad SS_{bst} = \frac{\sum_{f} Loan_{bfst}}{\sum_{s}\sum_{f} Loan_{bfst}} \tag{13}$$

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

Second, following Paravisini et al. (2023), we identify specialized banks using relative thresholds.[19] For each conflict country-year, we calculate the 75th percentile of bank lending

[19] We also experimented with alternative relative specialization measures put forward by Blickle et al. (2024) and obtained qualitatively similar results.

shares (α_{ct}). Banks exceeding this threshold are classified as country-specialized; those exceeding the analogous sector-specific threshold (α_{st}) are classified as sector-specialized:

$$RCS_{bct} = \begin{cases} 1, \text{ if } CS_{bct} \geq \alpha_{ct} \\ 0, \text{ if else} \end{cases} \qquad RSS_{bst} = \begin{cases} 1, \text{ if } SS_{bst} \geq \alpha_{st} \\ 0, \text{ if else} \end{cases} \tag{14}$$

where RCS and RSS stand for relative country and sector specialization, respectively.

In Table 7, we estimate Equation (8) separately for specialized and non-specialized cross-border lenders, using in both cases domestic lenders as the control group. Specifically, we first compare country-specialized foreign banks ($RCS_{bct} = 1$ and $Foreign = 1$) and country non-specialized foreign banks ($RCS_{bct} = 0$ and $Foreign = 1$) to domestic banks. Then, we repeat this analysis for sector specialization, comparing military-specialized and non-specialized foreign banks to domestic lenders.

The first two columns of Table 7 reveal distinct patterns based on country specialization. Both groups reduce non-military lending during conflicts, but their military lending responses diverge sharply. Country-specialized banks exhibit a comprehensive flight-home effect, reducing both military and non-military lending as they retreat from familiar but now-risky markets (net military effect: -20.7%). Non-specialized banks, however, selectively reallocate: while reducing non-military lending at similar rates, they increase military lending by 43.8%, consistent with opportunistic profit-seeking in unfamiliar markets where they face fewer reputational constraints. The difference between groups is significant at the 1% level (p-value = 0.006).

Columns (3) and (4) reveal the opposite pattern for military sector specialization. Both groups contract non-military lending by 24–26%, but their military responses diverge. Military-specialized banks increase defense-sector exposure by approximately 37%, leveraging established expertise to partially offset their general retrenchment. Non-specialized banks retreat comprehensively, reducing military lending by approximately 8.2% alongside their

Table 7. Bank specialization and cross-border lending during violent conflicts

	Dependent variable: $Loan_{bft}$					
Specialization:	Relative measure (Paravisini et al., 2023)					
	In country ($RCS_{bct}=1$)		*P*-value *diff=0*	In sector ($RSS_{bst}=1$)		*P*-value: *diff=0*
	Yes	No		Yes	No	
	(1)	(2)		(3)	(4)	
Foreign × Conflict	-0.515***	-0.434***	*0.714*	-0.303**	-0.271**	*0.843*
	(0.174)	(0.137)		(0.119)	(0.112)	
Foreign × Conflict × Military	0.283**	0.797***	*0.006*	0.617***	0.186	*0.056*
	(0.131)	(0.135)		(0.133)	(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	718,340	1,277,615		1,281,197	1,108,826	
N banks	10,601	13,765		13,902	13,279	
R^2 (adj.)	0.911	0.869		0.868	0.866	

Note: This table shows the results of our baseline specification (8) run on four sub-samples of banks: those relatively specialized in lending to particular countries ($RCS_{bct}=1$) and those that are not ($RCS_{bct}=0$), in the first two columns, and those relatively specialized in lending to military firms ($RSS_{bst}=1$) and those that are not ($RSS_{bst}=0$), in the last two columns. In all cases, the dependent variable is the natural logarithm of the loan amount. Relative specialization measures are defined by expressions (14), with the cutoff thresholds $\alpha_{ct}=\alpha_{st}=75^{th}$ 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 E.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.

non-military contraction. The difference is statistically significant (p-value = 0.056).

Overall, these results underscore how pre-existing geographical and sector expertise shape banks' lending responses during armed conflicts. The documented reallocation toward military sectors is driven by two distinct groups: (i) cross-border lenders with established military-sector expertise that increase defense lending despite reducing overall exposure, and (ii) cross-border lenders without country-specific relationships that increase military lending while retreating from non-military sectors. This suggests that conflict-induced military lending reflects both sector-specific expertise and opportunistic reallocation by banks with limited local relationships to protect.

6.3 Spillovers to neighboring countries

Does increased military lending to conflict countries spill over to the broader region? Wars can reshape regional security dynamics (Federle, Meier, Müller, Mutschler and Schularick, 2024), prompting neighboring states to bolster defense capabilities amid heightened uncertainty. This may increase demand for military equipment in adjacent countries, potentially leading cross-border lenders to expand defense-sector credit beyond primary conflict zones.

We manually identify neighbors of conflict countries from Appendix Table A.I, excluding cases where neighboring countries themselves experience major conflicts (>1,000 battlefield deaths threshold). For example, Pakistan and India cannot serve as neighbors for each other in 2008-2010 when both experienced major conflicts, though they qualify as neighbors in non-conflict years. This approach isolates whether cross-border military lending increases to a country solely due to its proximity to conflict, rather than its own involvement in hostilities.

In Table 8, we examine spillover effects by creating a dummy variable, *Neighbor*, for countries bordering conflict-affected nations but not experiencing major conflict themselves. Columns (1)-(4) apply increasingly stringent definitions of "non-conflict", from fewer than 1,000 battlefield deaths to zero deaths, isolating pure spillover effects. We find that cross-border lenders do not increase military lending to neighboring non-conflict regions, indicating banks react to conflicts rather than proactively target potential spillover zones. While columns (3)-(4) show foreign banks reduce non-military lending to low-conflict neighbors, the absence of corresponding military lending increases confirms that strategic military financing targets primary conflict zones rather than broader regional instability.

Table 8. Spillovers to neighboring countries

	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***	-0.102***
	(0.038)	(0.034)	(0.036)	(0.038)
Neighbor × Foreign × Military	0.063	-0.045	-0.020	-0.024
	(0.043)	(0.042)	(0.039)	(0.041)
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.)	0.867	0.867	0.867	0.867

Note: Estimates of Equation (8) for neighboring countries. Dependent variable: log loan amount. *Foreign* equals one for cross-border lending. *Neighbor* equals one for firms in countries bordering conflict countries. *Military* equals one for primary or dual-use military sectors (Table E.I). All regressions include fixed effects as specified. Data: UCDP and DealScan. ***, **, * denote significance at 1%, 5%, 10%. Standard errors clustered by bank in parentheses.

6.4 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. They may continue military financing if peace appears fragile or to deter future conflicts. Conversely, they may reduce military lending as defense sector profitability declines relative to reconstruction opportunities, government demand falls, or peace agreements impose new regulatory constraints on defense financing.

We define a new dummy variable *Post-*$Conflict$ equal to 1 in the first, second, or third year after hostilities end. Table 9 reports Equation (8) with interactions of this variable with $Foreign$ and $Military$. Since we retain $Conflict$ × $Foreign$ × $Military$, the new triple interaction measures changes in cross-border military lending relative to pre-conflict levels.

Table 9. 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	-0.026	0.098	0.200*
	(0.148)	(0.136)	(0.118)
Post-Conflict × Foreign × Military	0.796***	0.547***	0.077
	(0.172)	(0.194)	(0.178)
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.)	0.867	0.86	0.867

Note: Estimates of Equation (8) for post-conflict periods. Dependent variable: log loan amount. *Foreign* equals one for cross-border lending. *Post-Conflict* equals one if the firm's country had >1,000 battlefield deaths one year prior (col. 1), two years prior (col. 2), or three years prior (col. 3), but no current conflict. *Military* equals one for primary or dual-use military sectors (Table E.I). All regressions include *Conflict* interactions and fixed effects as specified. Data: UCDP and DealScan. ***, **, * denote significance at 1%, 5%, 10%. Standard errors clustered by bank in parentheses.

Cross-border lenders' military lending advantage persists in the first post-conflict year (column 1), weakens in year two (column 2), and disappears by year three (column 3), aligning with Figure 2. Meanwhile, $Post\text{-}Conflict \times Foreign$ becomes increasingly positive and significant by year three (column 3), indicating cross-border lenders gradually re-enter conflict-affected markets through non-military lending as reconstruction opportunities emerge, reversing their initial flight-home behavior. These results show foreign banks' military lending advantage is temporally bounded, concentrated during active conflict when defense demand peaks and domestic financial capacity is constrained. Once conflicts end, foreign banks reallocate from military to civilian lending as defense profitability declines and reconstruction opportunities increase.

6.5 Geographical distance to violent conflicts

Does geographical distance affect foreign banks' propensity to lend to military sectors? Recent evidence shows that countries located near conflict zones experience severe economic losses – GDP falls by more than 10% and inflation rises by about 5 percentage points – whereas more distant countries face limited or even positive spillovers (Federle et al., 2024). These patterns generate competing hypotheses: distant banks may better exploit heightened military credit demand due to insulation from conflict-related risks and scrutiny, while nearby banks may benefit from superior local information.

Table 10 tests these hypotheses by replacing the $Foreign$ dummy with the logarithm of the geographical distance between bank and borrower capital cities (set to zero for domestic banks). Consistent with a financial gravity model, the first two rows show that cross-border lending declines with distance, an effect that is stronger for conflict countries. In contrast, columns (2)–(3) reveal the opposite pattern for military lending: the effect increases with distance. This result is robust across specifications. The coefficient of 0.057 in column (3) implies that military lending to a conflict country rises by about 4.0% for a bank located 2,000 kilometers away relative to one located 1,000 kilometers away.

Overall, the results suggest that geographical distance attenuates reputational and regulatory constraints when financing military projects in conflict zones. Reduced scrutiny from domestic stakeholders (such as regulators, media, and the general public) may allow distant banks to pursue military-sector lending opportunities more aggressively than geographically proximate banks.

Table 10. 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	-0.019	-0.029**	-0.028**
	(0.014)	(0.014)	(0.014)
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.)	0.867	0.867	0.867

Note: Estimates of Equation (8) with geographical distance as key variable. Dependent variable: log loan amount. *Distance*: log geographical distance between lender's home country and borrower's country. *Conflict* equals one for >1,000 battlefield deaths per year. *Military* equals one for primary or dual-use military sectors (Table E.I). All regressions include fixed effects as specified. Data: UCDP, DealScan, CEPII GeoDist. ***, **, * denote significance at 1%, 5%, 10%. Standard errors clustered by bank in parentheses.

6.6 The role of lender type and bank ownership

A final natural extension of our analysis is to examine heterogeneity across lender types and ownership structures. The expected differences between banks and non-banks are theoretically ambiguous: banks have deeper internal capital markets enabling resource reallocation, but face stricter regulations that may constrain military lending in conflict zones. Bank ownership represents another important dimension. An extensive literature shows public and private banks exhibit distinct lending patterns due to political influences (Claessens, Feijen and Laeven, 2008; Bircan and Saka, 2021; Koetter and Popov, 2021). If political incentives drive military lending, state-owned banks may respond more to these pressures, potentially explaining our findings on foreign bank behavior and the differences between western and eastern banks documented in Section 6.1.

Table 11. 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}	-0.317*** (0.116)	-0.223** (0.094)
Conflict × $\mathbb{X}_{2,bft}$	β_{12}	-0.047 (0.141)	-0.230** (0.094)
Conflict × Military × $\mathbb{X}_{1,bft}$	β_{21}	0.522*** (0.104)	0.544*** (0.126)
Conflict × Military × $\mathbb{X}_{2,bft}$	β_{22}	0.476* (0.248)	0.535** (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	1,172,767
N lenders		14,021	8,936
R^2 (adj.)		0.867	0.876
Share of $\mathbb{X}_{2,b,f,t}$ in the full sample		10%	8%
P-value of the linear test: $\beta_{11} = \beta_{12}$		*0.004*	*0.887*
P-value of the linear test: $\beta_{21} = \beta_{22}$		*0.840*	*0.930*

Note: Dependent variable: log loan amount. *Conflict* equals one for >1,000 battlefield deaths per year. *Military* equals one for primary or dual-use military sectors (Table E.I). Column (1): banks ($\mathbb{X}_{1,bft}$) vs non-banks ($\mathbb{X}_{2,bft}$) in cross-border lending. Column (2): private ($\mathbb{X}_{1,bft}$) vs public banks ($\mathbb{X}_{2,bft}$). All regressions include fixed effects as specified. Data: UCDP and DealScan. ***, **, * denote significance at 1%, 5%, 10%. Standard errors clustered by bank in parentheses.

Table 11 analyzes both dimensions. Column (1) shows banks and non-banks both increase military lending in conflict countries to a similar extent, though banks exhibit a stronger flight-home effect (p-value = 0.01). Column (2) shows both private and state-owned banks reduce non-military lending while increasing military lending during conflicts, suggesting similarly motivated responses to profit opportunities regardless of political alignment.

7 Conclusions

We examine how violent conflicts affect cross-border lending, focusing on credit allocation to military-related sectors. While Horn et al. (2024) show that sovereigns finance wars primarily through official allied credit, little is known about how private lenders respond. Using syndicated loan data covering 14,021 lenders and 97,169 firms across 179 countries during 1989–2020, we document a parallel private channel characterized by two main patterns. First, cross-border lenders reduce aggregate credit to conflict-affected countries relative to domestic banks, consistent with a flight-home response. Second, despite this aggregate contraction, they simultaneously expand lending to military-sector firms, redirecting capital toward defense and dual-use industries during conflicts.

This reallocation is economically significant, robust to other definitions of conflict and military sector classification, and equally strong for bank and non-bank creditors. The pattern largely reflects heightened credit demand among military firms that cross-border lenders are better positioned to accommodate, while the retreat from non-military lending is mainly supply-driven. The effect is strongest among lenders with military-sector expertise but limited country specialization, and among creditors from geopolitically non-aligned countries.

Our results take on heightened relevance amid intensifying geopolitical fragmentation. NATO members have committed to sustained increases in military spending, European nations are undertaking their largest defense buildup since the Cold War, and these commitments translate into substantial financing needs for firms manufacturing defense equipment and dual-use technologies. While rising geopolitical distance generally discourages cross-border capital allocation, we reveal an important exception: lending to military sectors *increases* during conflicts, particularly from geopolitically distant lenders. This selective persistence suggests that the "weaponisation of finance" operates through channels beyond sanctions and payment-system restrictions.

We can think of several directions for future research. One is examining how foreign credit access affects not only corporate performance but also the intensity and duration of hostilities. A second is to study the interaction between cross-border lenders and domestic banking systems during wartime, including whether foreign retrenchment amplifies local financial constraints or whether international lenders partially substitute for impaired domestic credit supply. A third concerns the intertemporal consequences of wartime credit reallocation: increased financing of military and dual-use sectors may crowd out investment in civilian industries, potentially slowing post-conflict recovery and reconstruction.

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Appendix A Brief descriptions of violent conflicts

Table A.I. Description of violent conflicts occurred in 1989–2020, by countries with $\geq$ 1,000 deaths (*beginning*)

Country	Conflict Years	Conflict ID	Conflict Description
Panel 1: Countries with > 0 syndicated loans during at least one conflict year			
Algeria	1994–1999	386	Algeria experienced a brutal armed conflict in the 1990s following the cancellation of the 1991 elections, which an Islamist party was expected to win. The ensuing civil war pitted the government against Islamist armed groups seeking to establish an Islamic state by force. Violence peaked between 1994 and 1999, marked by large-scale massacres, bombings, and severe repression. Groups such as the Armed Islamic Group (GIA) and the Islamic Salvation Army (AIS) were central actors during this period. By the early 2000s, hostilities had largely subsided as some groups disarmed and state control was reasserted.
Angola	1989, 1990, 1992, 1993, 1994, 1998, 1999, 2001	327; 387	Angola's post-independence period was dominated by two overlapping conflicts: the long-running civil war (1975–2002) between the ruling MPLA and the opposition UNITA, and the Cabinda separatist insurgency led by the Front for the Liberation of the Enclave of Cabinda (FLEC). The civil war, fueled by Cold War rivalries and regional interventions, caused massive civilian casualties and destruction during the late 1980s and 1990s. The Cabinda insurgency, focused on control over the province's oil resources, continued sporadically throughout the same period. The conflicts effectively ended after UNITA leader Jonas Savimbi's death in 2002 and the signing of a peace accord.
Colombia	1992, 1994, 1996, 1999–2005	289	Colombia's long-running internal conflict involved the government, leftist guerrilla movements such as the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN), and right-wing paramilitary groups. Beginning in the 1960s and intensifying through the 1990s and early 2000s, the conflict was rooted in inequality, land distribution, and political exclusion. The period from the early 1990s to mid-2000s saw widespread violence and displacement, much of it financed by drug trafficking. The signing of a 2016 peace agreement with FARC formally ended decades of armed confrontation, though violence persists in some regions.
Congo, DR	1996–2000, 2009, 2013–2014, 2017, 2020	265; 283; 314; 374; 429; 14692	The Democratic Republic of Congo has experienced repeated large-scale conflicts involving both domestic and foreign actors. The First (1996–1997) and Second (1998–2003) Congo Wars drew in numerous neighboring states and resulted in millions of deaths from violence, hunger, and disease. Rebel groups such as the AFDL, RCD, and later M23, as well as forces from Rwanda and Uganda, have fought the government over power, territory, and resources. Subsequent years saw continued instability in the east, including operations by the Allied Democratic Forces (ADF), Kata Katanga, and armed groups linked to the Islamic State. Despite peace accords and formal war endings, violence has persisted in parts of the country.
Ethiopia	1989–1991, 1999–2000, 2020	267; 275; 329; 413; 11447	Ethiopia has experienced several major conflicts over recent decades. In the late 1980s and early 1990s, the Derg regime collapsed after prolonged fighting with the Ethiopian People's Revolutionary Democratic Front (EPRDF) and the Eritrean People's Liberation Front (EPLF), culminating in Eritrea's independence in 1993. Renewed interstate hostilities with Eritrea followed in 1998–2000 over disputed borders, causing heavy casualties before the Algiers peace agreement. Most recently, in 2020, war broke out between the Ethiopian government and the Tigray People's Liberation Front (TPLF), leading to severe humanitarian and economic crises before a ceasefire was reached in 2022.
India	1989–1994, 1999–2010	218; 227; 251; 335; 347; 351; 364; 365; 421; 434; 11342; 11475	India has experienced multiple internal armed conflicts involving separatist, ethnic, and ideological insurgent groups. In the northeast, rebel movements rooted in tribal and ethnic identities have fought the government in states such as Assam, Nagaland, Tripura, and Manipur. India has also confronted Sikh separatists in Punjab and various insurgent groups in Jammu and Kashmir, where territorial claims overlap with Pakistan. Left-wing communist movements—including the MCC, PWG, and later CPI-Maoist—have waged prolonged insurgencies across central and eastern regions. In addition to these internal conflicts, India has faced an interstate dispute with Pakistan over Kashmir—a single territorial confrontation that has generated several bouts of armed hostilities during those years.

Table A.I. Description of violent conflicts occurred in 1989–2020, by countries with $\geq$ 1,000 deaths (*continuing*)

Country	Conflict Years	Conflict ID	Conflict Description
Iraq	1991, 1997, 2003–2011, 2013–2018	259; 271; 338; 354; 371; 420	Iraq has faced repeated episodes of major armed conflict. The 1991 Gulf War erupted after Iraq's invasion of Kuwait and resulted in extensive destruction. In the late 1990s, clashes occurred between Iraqi forces and Kurdish groups in the north. The 2003 U.S.-led invasion toppled Saddam Hussein but was followed by years of insurgency, civil conflict, and sectarian violence. From 2013 onward, the Islamic State (IS) seized significant territory in Iraq, triggering large-scale military operations by Iraqi forces, Kurdish Peshmerga, and an international coalition. By 2018, IS had lost most territorial control, though pockets of insurgent activity persisted.
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	Liberia's Second Civil War (1999–2003) saw the government of President Charles Taylor fight rebel groups including LURD (Liberians United for Reconciliation and Democracy) and MODEL (Movement for Democracy in Liberia). The conflict was fueled by ethnic and political grievances, regional interference, and competition over resources. Widespread atrocities led to a humanitarian crisis and international intervention. The war ended with Taylor's resignation, the Accra Peace Agreement, and the deployment of UN peacekeeping forces to restore order and oversee democratic transition.
Nigeria	2013–2020	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	2008–2015	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 occurred in 1989–2020, by countries with $\geq$ 1,000 deaths (*continuing*)

Country	Conflict Years	Conflict ID	Conflict Description
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	1990–1993, 1995-2001, 2006-2009	313; 352	The civil war between the Sri Lankan government and the Liberation Tigers of Tamil Eelam (LTTE) lasted from 1983 to 2009. The LTTE sought to establish an independent Tamil state in the north and east of the island. The conflict was marked by protracted fighting, suicide bombings, and large-scale offensives, with major escalations in the early 1990s and again in the 2000s. The war ended in May 2009 with the military defeat of the LTTE, following an intense final phase that resulted in significant civilian casualties.
Türkiye	1992–1999, 2016	338; 354; 383; 13902	Türkiye has experienced recurring armed conflict primarily involving the state and the PKK, whose insurgency escalated in the 1990s through intense clashes, security operations, and widespread displacement. Smaller far-left groups such as the DHKP-C also conducted sporadic attacks on state institutions. In 2016, violence took several forms: renewed fighting with the PKK, major ISIS attacks in Istanbul and other cities, and a separate coup attempt by a faction of the military that caused significant casualties and nationwide disruption.
Ukraine	2014, 2015	13219;13243; 13246; 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.

Table A.I. Description of violent conflicts occurred in 1989–2020, by countries with $\geq$ 1,000 deaths (*continuing*)

Country	Conflict Years	Conflict ID	Conflict Description
Panel 2: Countries with no syndicated loans during conflict years			
Azerbaijan	1992, 1993, 1994, 2020	388; 396	The Nagorno-Karabakh conflict between Azerbaijan and ethnic Armenian forces in the region of Nagorno-Karabakh centers on questions of territorial control and self-determination. Heavy fighting in the early 1990s, following the collapse of the Soviet Union, resulted in Armenian forces taking control of Nagorno-Karabakh and surrounding districts. Renewed war in 2020 saw Azerbaijan recapture substantial territories through large-scale military operations, supported in part by advanced weaponry and Turkish assistance, before a Russian-brokered ceasefire halted the fighting.
Bosnia and Herzegovina	1992–1995	389; 390; 397; 398	The Bosnian War (1992–1995), part of the breakup of Yugoslavia, involved Bosnia's government and Bosnian Serb, Croat, and Bosniak forces. The conflict was marked by ethnic cleansing, sieges, and large-scale atrocities, including the Srebrenica massacre. NATO intervention in 1995 and the Dayton Peace Agreement ended the fighting and established Bosnia and Herzegovina as a single state composed of two entities.
Burundi	2000–2002	287	The Burundian Civil War (1993–2005) pitted Hutu rebel movements — notably the CNDD-FDD and Palipehutu-FNL — against the Tutsi-dominated government, grounded in deep ethnic divisions. Fighting peaked around 2000, and a series of agreements culminating in the Pretoria Protocol (2003) introduced power-sharing and integration of rebel forces into government structures, substantially reducing large-scale hostilities by the mid-2000s.
Chad	2006	288	Chad experienced renewed internal conflict in 2006 as rebel coalitions, including the United Front for Democratic Change (UFDD), attempted to overthrow President Idriss Déby. Fighting centered in eastern Chad and was fueled by cross-border tensions and spillover from the Darfur conflict in neighboring Sudan. Government forces ultimately repelled the insurgents, though sporadic clashes persisted in subsequent years.
Congo	1997–1998	408	The Republic of Congo's civil war (1997–1998) pitted militias loyal to President Pascal Lissouba against forces aligned with former President Denis Sassou Nguesso. Backed by Angolan troops, Sassou Nguesso's Cobra militia captured Brazzaville after intense fighting that caused thousands of deaths and widespread destruction. Sassou Nguesso regained power, and although organized combat ended, low-level insurgency continued in parts of the country in the following years.
El Salvador	1989	316	The Salvadoran Civil War (1979–1992) involved the government and the leftist Farabundo Martí National Liberation Front (FMLN), rooted in inequality and authoritarian rule. By the late 1980s, violence peaked with large-scale clashes and massacres. The 1992 Chapultepec Peace Accords ended the conflict, integrating FMLN as a political party.
Eritrea	1999–2000	326; 409	The Eritrean–Ethiopian War (1998–2000) was an interstate conflict over the disputed Badme border region. Both countries mobilized large armies, leading to tens of thousands of casualties before the Algiers Agreement ended active hostilities in December 2000. Although fighting ceased, the border remained tense for years, with full normalization of relations occurring only in 2018.
Georgia	1993	380; 392	Georgia faced separatist conflicts following independence from the Soviet Union. In 1992–1993, fighting in Abkhazia between Georgian government forces and Abkhaz separatists, supported by Russian elements, led to massive displacement of ethnic Georgians. A ceasefire left Abkhazia as a de facto independent entity.
Kuwait	1990	371	The 1990 Iraqi invasion of Kuwait triggered the Gulf War. Iraqi forces occupied Kuwait for seven months until a U.S.-led coalition expelled them in early 1991. The war caused extensive infrastructure destruction and loss of life, leaving Kuwait dependent on coalition protection during post-war reconstruction.

Table A.I. Description of violent conflicts occurred in 1989–2020, by countries with $\geq$ 1,000 deaths (*continuing*)

Country	Conflict Years	Conflict ID	Conflict Description
Libya	2011, 2016, 2019	11346; 13694	Libya's 2011 uprising against Muammar Gaddafi evolved into a civil war, with NATO intervention aiding rebel forces that ultimately toppled the regime. After 2014, rival governments in Tripoli and Tobruk vied for control, supported by competing militias and foreign backers. Fighting in 2016 and 2019 involved battles between the Government of National Accord and the Libyan National Army, as well as clashes with Islamic State affiliates.
Mozambique	1989–1991	332	Mozambique's post-independence civil war (1977–1992) pitted the ruling FRELIMO government against the RENAMO insurgency, originally supported by Rhodesia and apartheid South Africa. The war devastated rural areas and caused severe humanitarian crises. The 1992 Rome General Peace Accords ended major fighting, paving the way for democratic elections.
Myanmar	1989, 1992	221; 222; 231; 253	Myanmar's internal conflicts are driven by longstanding ethnic insurgencies, particularly among Karen, Kachin, and Karenni groups seeking autonomy or independence. After the 1988 uprising, the military junta intensified operations against these movements, leading to renewed clashes in the late 1980s and early 1990s. Although several ceasefires were signed during the 1990s, fighting continued intermittently in various border regions.
Nepal	2002–2005	269	Nepal's Maoist insurgency (1996–2006) aimed to replace the monarchy with a communist republic. The conflict involved rural guerrilla warfare and government counterinsurgency campaigns, causing widespread displacement and casualties. The 2006 Comprehensive Peace Accord ended the war and integrated Maoist forces into the political process.
Peru	1989–1992	292	Peru's internal conflict with the Shining Path (Sendero Luminoso), a Maoist insurgent group, peaked between the late 1980s and early 1990s. The group sought to overthrow the state through violent revolution. The capture of its leader Abimael Guzmán in 1992 marked a turning point, leading to a sharp decline in violence.
Rwanda	1990, 1994, 1998, 2001	374	The Rwandan Civil War (1990–1994) began with the invasion of the Rwandan Patriotic Front (RPF), a Tutsi-led rebel movement, against the Hutu-dominated government. The conflict culminated in the 1994 genocide, in which extremists killed around 800,000 people, before the RPF seized power and ended the mass killings. In the late 1990s and early 2000s, Rwanda also became involved in cross-border fighting linked to the Congo wars, contributing to continued regional instability.
Serbia (Yugoslavia)	1991, 1998, 1999	385; 412	During the breakup of Yugoslavia, Serbia—then part of the Federal Republic of Yugoslavia—was involved in several conflicts. In 1991, Serbian/Yugoslav forces fought in Croatia amid territorial disputes and ethnic tensions. Later, the Kosovo conflict (1998–1999) pitted Serbian/Yugoslav security forces against Kosovo Albanian separatists, escalating into widespread violence and triggering NATO's 1999 air campaign, which led to Serbia's withdrawal from Kosovo.
Sierra Leone	1995, 1998, 1999	382	The Sierra Leone Civil War (1991–2002) involved government forces and the Revolutionary United Front (RUF), notorious for atrocities including mass killings and amputations. Supported by diamond revenues, the conflict destabilized the country until British and UN intervention helped end hostilities in 2002.
Sudan	1989–1992, 1995–2004, 2006, 2010–2012, 2015, 2016	288, 309; 314; 11344	Sudan's long-running north–south civil war pitted the Khartoum government against the Sudan People's Liberation Movement/Army (SPLM/A), driven by ethnic, religious, and economic divisions. Although a 2005 peace agreement ended this conflict and led to South Sudan's independence, new violence emerged in Darfur during the early 2000s and later in South Kordofan and Blue Nile, where the government fought various rebel groups including the SPLM-North. These overlapping conflicts continued intermittently into the 2010s.

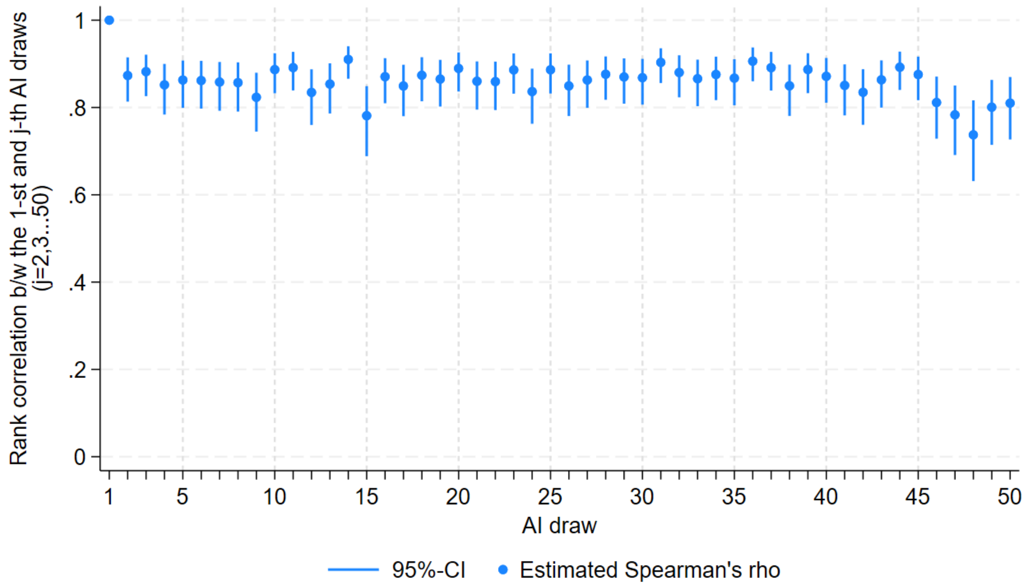
Table A.I. Description of violent conflicts occurred in 1989–2020, by countries with $\geq$ 1,000 deaths (*ending*)

Country	Conflict Years	Conflict ID	Conflict Description
Syria	2011–2020	259; 299; 418; 426; 13042; 13604; 13809; 13886; 13902; 14609	The Syrian Civil War began with protests against President Bashar al-Assad in 2011 and rapidly escalated into a multi-sided conflict involving the government, diverse rebel factions, Kurdish forces, and Islamist groups such as ISIS. Foreign interventions by Russia, Iran, Turkey, and the United States further intensified and prolonged the fighting. By the late 2010s, the Assad government had reestablished control over most of the country, although violence and localized clashes continued.
Tajikistan	1992, 1993, 1996	395	The Tajik Civil War broke out shortly after independence, pitting the post-communist government against the United Tajik Opposition (UTO), a coalition of Islamist and regional groups. The conflict caused severe economic disruption and massive displacement. A 1997 peace agreement introduced power-sharing arrangements and brought major hostilities to an end.
Uganda	1989, 1996, 2004	314	Uganda faced multiple insurgencies, including the Lord's Resistance Army (LRA) led by Joseph Kony, known for brutal tactics and child abductions. Concentrated in the north, the conflict caused large-scale displacement and humanitarian crises. Government offensives in the mid-2000s pushed the LRA out of Uganda, reducing violence.
Yemen	1994, 2011, 2012, 2014–2020	230; 402; 13645	Yemen has experienced recurrent conflicts shaped by regional, sectarian, and political divisions. The 1994 civil war erupted after the unification of North and South Yemen, while renewed unrest in 2011–2012 accompanied the Arab Spring and transition of power. The conflict escalated sharply after 2014, when Houthi forces seized Sana'a and a Saudi-led coalition intervened. Fighting has involved multiple actors—including southern separatists, tribal militias, and Al-Qaeda and Islamic State affiliates—and has produced one of the world's worst humanitarian crises.

Note: This table summarizes conflict-affected countries that were (*Panel 1*) or were not (*Panel 2*) active participants in the syndicated loan market during the conflict years. Panel 1 presents the 16 conflict-affected countries included in our loan-level analysis in the main text; these countries remain in our dataset after merging UCDP with Dealscan. Panel 2 lists an additional 22 countries that experienced conflicts with at least 1,000 battle-related deaths in certain years but did not borrow through the syndicated loan market during those periods. We use these 22 countries, together with the 16 countries in Panel 1, in our aggregate-level analysis in Section 5.1. For both panels, the table reports the corresponding conflict ID(s) from the UCDP dataset and provides brief descriptions of each conflict. The primary data source is UCDP, supplemented with 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
Loan_{gsct}	The amount of syndicated loans aggregated to the bank group (g)-sector (s)-country (c)-year (t) level, where g is 1 for foreign banks and 0 for domestic lenders and s is 1 for military and 0 for civilian sectors (defined below)	DealScan & Authors' calculations	0 or $US
Loan_{bfsct}	The log of the amount of syndicated loan extended by bank b within the syndicate of lenders to firm f operating in sector s in year t (actual data, where available, or imputed data based on each bank's historical average share from loans with known allocations)	DealScan & Authors' calculations	Log $US
Foreign	$Dummy = 1$ if country of the bank $\neq$ the country of the firm	DealScan & Authors' calculations	0/1
Military	$Dummy = 1$ if the firm's SIC code pertains to either primary or dual-use SIC codes, as defined in Table E.I.	DealScan, Compustat, NAICS/SIC website & Authors' calculations	0/1
Battlefield deaths	Battle-field related deaths per country and year.	Uppsala Conflict Data Program (UCDP)	Persons
Conflict ($\jmath$)	$Dummy = 1$ if battle-field related deaths per country and year are greater than or equal to $\jmath = 1,000\,(baseline), 750, 500, 250$.	UCDP & Authors' calculations	0/1
Post-conflict	$Dummy = 1$ for the year(s) after a conflict, i.e., when the number of deaths decreases below the 1,000 threshold	UCDP & Authors' calculations	0/1
Relative specialization in conflict country RCS (military sector RSS)	$Dummy = 1$ if a cross-border lender's country share CS (military sector share SS) is in the upper quartile of all cross-border lenders that lend to that country (military sector) in a given year	DealScan & Authors' calculations	0/1
NATO (G7) (BRICS)	$Dummy = 1$ if a country belongs to NATO (G7) (BRICS)	Wikipedia	0/1
UN West (East)	Countries that vote similarly (oppositely) to the US in the UN General Assembly, i.e., in the bottom (upper) 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
(Capital) distance	Distance between the capital of the bank country and capital of the firm country	CEPII GeoDist	Log km
Debt	The log of the book value of all interest-bearing financial obligations of firm f in year t with maturity ≥ 1 year ($dltt$)	Compustat US+Global	Log $US
Borrowing	$Dummy = 1$ if firm f had domestic or cross-border loans during the last two pre-conflict years in Dealscan or 0 if firm f was observed only in Compustat and had positive $Debt$ over the same horizon	DealScan & Compustat & Authors' calculations	0/1
Foreign Share	The sum of firm f cross-border loans over the last two pre-conflict years divided by the sum of total loans over the same horizon if firm f is observed in Dealscan or 0 if firm f is observed only in Compustat and has positive $Debt$ over the same horizon	DealScan & Compustat & Authors' calculations	%
EBIT	Earnings before interest and taxes, representing firm's f ability to generate earnings from operations, independent of its capital structure or tax environment.	Compustat US+Global & Authors' calculations	% of total assets (at)
Employment	The number of full or part-time employees at firm f in year t (emp)	Compustat US+Global	Log ths of persons
Revenue	The gross sales and other operating revenue of firm f in year t before deducting any costs, returns, or allowances ($revt$)	Compustat US+Global	Log $US
Tangible assets	The book value of tangible fixed assets net of accumulated depreciation of firm f in year t ($ppent$, Property, Plant, and Equipment – Total (Net))	Compustat US+Global	Log $US

Appendix D Descriptive statistics

Table D.I. Descriptive statistics

	N	Mean	SD	Min	25th	Median	75th	Max
Main variables								
Loan_{gsct} (*bn* $US)	22,912	1.70	8.43	0	0	0	0.13	86.89
Loan_{bfsct} (log)	1,324,617	16.48	2.43	8.93	15.86	17.09	18.02	20.27
Foreign	1,324,617	0.47	0.50	0	0	0	1	1
Military (primary & dual)	1,324,617	0.169	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	0.168	0.37	0	0	0	0	1
Deaths	1,324,617	36.38	216.64	0	0	0	0	10,211
Conflict dummy (1,000)	1,324,617	0.01	0.10	0	0	0	0	1
Conflict dummy (500)	1,324,617	0.02	0.15	0	0	0	0	1
EBIT[a] (% of total assets)	1,008,369	0.81	19.47	-83.07	0	4.19	9.34	28.43
Revenue[a] (log)	967,895	6.25	3.53	-6.90	4.02	6.18	8.42	25.49
Revenue[b] (log)	3,467	5.68	2.53	0.70	4.09	5.87	7.57	9.59
Tangible assets[b] (log)	3,469	4.59	2.67	0	2.79	4.69	6.72	8.71
Employment[b] (log)	850	6.42	1.93	2.94	5.07	6.50	7.96	9.44
Debt[b] (log)	3,469	3.79	2.82	0	0.96	3.89	6.11	8.28
Foreign share[b]	4,222	0.019	0.133	0	0	0	0	1
Borrowing (0/1)[b]	4,222	0.023	0.182	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 (RCS_{bct})	1,324,617	0.19	0.39	0	0	0	0	1
Bank-(military) sector relative (RSS_{bst})	1,324,617	0.22	0.41	0	0	0	0	1
Others								
Neighbor	1,324,617	0.04	0.19	0	0	0	0	1
Post-conflict	1,324,617	0.01	0.10	0	0	0	0	1
Capital distance	1,323,023	3.81	4.16	0	0	0	8.68	9.90
Foreign bank	1,324,617	0.43	0.50	0	0	0	1	1
Foreign nonbank	1,324,617	0.03	0.18	0	0	0	0	1
Foreign private bank	1,189,084	0.44	0.50	0	0	0	1	1
Foreign public bank	1,189,084	0.04	0.20	0	0	0	0	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, Compustat, and CEPII GeoDist.

[a] All firms in Compustat.

[b] Firms observed before and after conflicts in Compustat only or in both Compustat and DealScan (conflict-affected countries only).

Appendix E Primary and dual-use military sectors

Table E.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

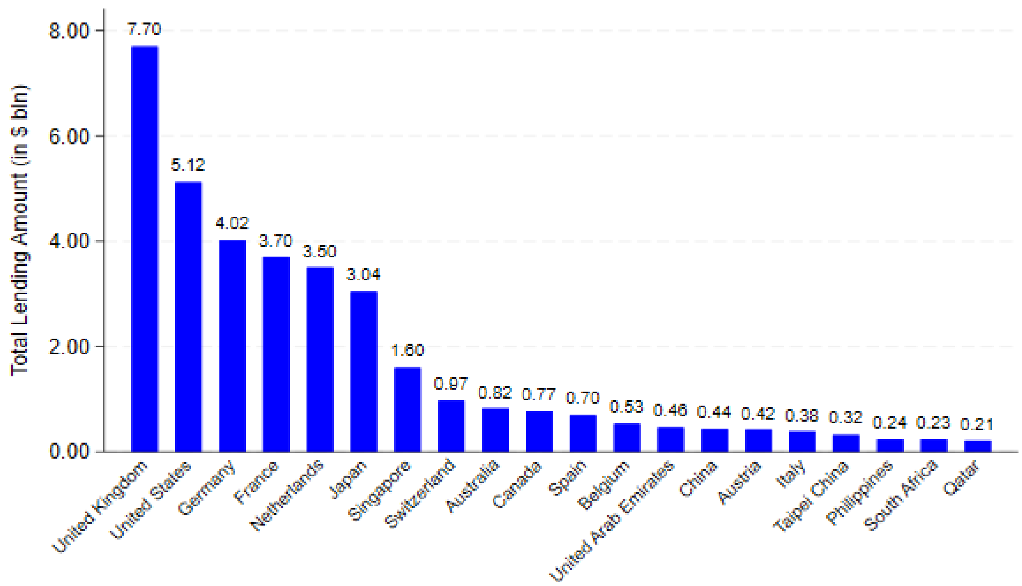
3357	Drawing and Insulating of Nonferrous Wire
3369	Nonferrous Foundries, Except Aluminum and Copper
3463	Nonferrous Forgings
3492	Fluid Power Valves and Hose Fittings
3511	Steam, Gas, and Hydraulic Turbines, and Turbine Generator Set Units
3519	Internal Combustion Engines, Not Elsewhere Classified
3536	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", and "defense") and dual-use (e.g. "telecommunications" and "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. The same SIC code can appear under several dual-use categories in Panel B. The unique-code count is calculated after removing such duplicates.

Appendix F Syndicated credit to military sectors: Main source countries

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

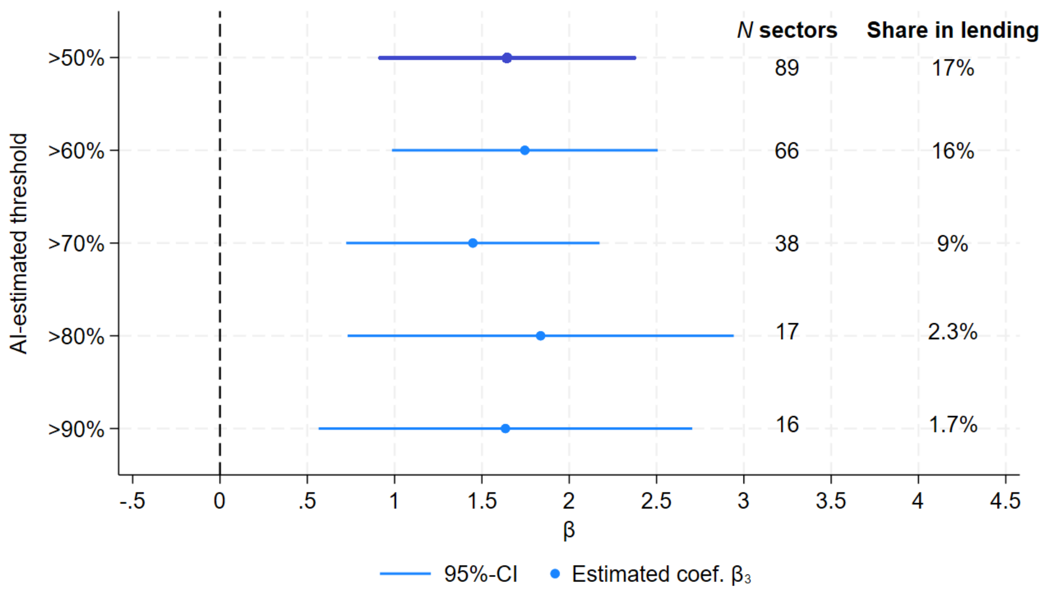


Note: This figure shows top-20 home countries in terms of the absolute amount (in $) of military-related lending to conflict countries during a violent conflict (1989–2020). Violent conflict is defined as a situation in which a country experiences more than 1,000 battle-field related deaths in a calendar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

Appendix G Robustness tests

This appendix describes the various robustness tests we subject our baseline aggregate-level and firm-level results to. We first examine the robustness of our aggregate-level 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 G.I illustrates that the point estimate of β_3 remains robust across thresholds even as the number of military sectors declines and their share in syndicated lending shrinks.

Figure G.I. Estimates at the aggregate level using different subsets of dual-use sectors

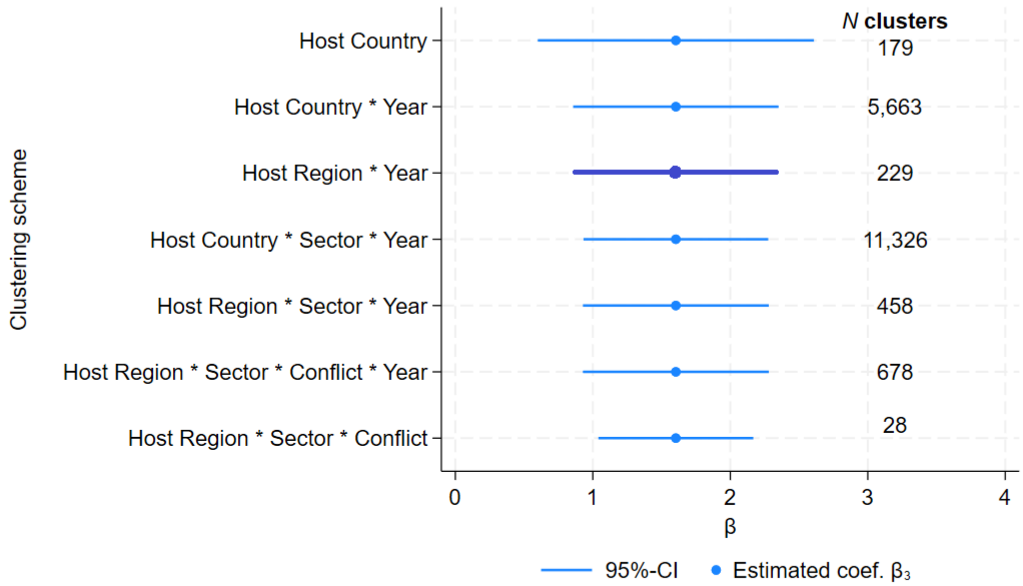


Note: This figure reports estimates of β_3 from the triple interaction Conflict × Foreign × Military in Equation (7), with 95% confidence intervals based on standard errors clustered by host region × year. We vary the AI-assigned probability threshold for classifying dual-use sectors from 50% to 90% in 10 pp increments. Each point represents a different threshold, with the baseline 50% threshold marked in dark blue. *N sectors* reports the number of military-related SIC codes at each threshold; *Share in lending* reports their share of total syndicated lending. *Conflict* indicates countries with >1,000 battlefield deaths per year. Data: Uppsala Conflict Data Program and DealScan.

Second, we check the robustness of our inference to different clustering approaches. Figure G.II compares the baseline approach (clustering at the level of host-country regions × year) to six alternatives: (i) host-country clusters; (ii) host-country × year clusters; (iii) host-country × sector × year clusters; (iv) host region × sector × year clusters; (v) host region

$\times$ sector $\times$ conflict $\times$ year clusters; and (vi) host region $\times$ sector $\times$ conflict clusters. As Figure G.II indicates, our β_3 estimate remains statistically significant at the 5% level (and, in fact, at the 1% level) in each case.

Figure G.II. Estimates at the aggregate level using different clustering of standard errors



Note: This figure displays the baseline estimate of β_3 from the triple interaction Conflict $\times$ Foreign $\times$ Military (Equation 7, Table 1) with 95% confidence intervals under alternative clustering schemes. The baseline uses host region $\times$ year clustering (dark blue). *Host* (*Home*) refers to the destination (origin) country of credit; *Region* represents the following regions: *ECA* is Europe and Central Asia, *EAP* is East Asia and Pacific; *NA* is North America, *LAC* is Latin America and the Caribbean; *MENA* is Middle East and North Africa; *SAR* is the South Asia region; *SSA* is Sub-Saharan Africa, and the rest. *Conflict* indicates countries with >1,000 battlefield deaths per year. Data: Uppsala Conflict Data Program and DealScan.

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 Table G.I , the results remain qualitatively unchanged.

Table G.I. Aggregate-level analysis:
Alternative transformation of the dependent variable

		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 region × 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

Note: Poisson Pseudo-Maximum Likelihood estimates with high-dimensional fixed effects (Correia et al., 2020). The dependent variable is the inverse hyperbolic sine transformation of total loans: $\ln(y + \sqrt{y^2 + 1})$, winsorized at the 99.5th percentile. $Foreign_{gc}$ equals one for cross-border lending. *Conflict* indicates >1,000 battlefield deaths per year. *Military* identifies military-related SIC sectors (Table E.I). *Host Region* includes the following regions: *ECA* is Europe and Central Asia, *EAP* is East Asia and Pacific; *NA* is North America, *LAC* is Latin America and the Caribbean; *MENA* is Middle East and North Africa; *SAR* is the South Asia region; *SSA* is Sub-Saharan Africa, and the rest. All regressions include fixed effects as specified. ***, **, * indicate significance at 1%, 5%, and 10%. Data: UCDP and DealScan. Standard errors clustered by host region × year level are shown in parentheses.

Fourth, we estimate a specification in which the dependent variable is the share of military loans by bank group g in country c and year t, relative to total lending in that country and year. This addresses 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. Table G.II shows we continue to find a positive and significant coefficient on $Foreign \times Conflict$: cross-border lenders increase the share of lending allocated to military sectors in countries with violent conflict.

Table G.II. 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 Poisson Pseudo-Maximum Likelihood estimations 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 E.I for the relevant SIC codes). All regressions include fixed effects as specified. *Host Region* includes the following regions: *ECA* is Europe and Central Asia, *EAP* is East Asia and Pacific; *NA* is North America, *LAC* is Latin America and the Caribbean; *MENA* is Middle East and North Africa; *SAR* is the South Asia region; *SSA* is Sub-Saharan Africa, and the rest. Data sourced from UCDP and DealScan. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by host region × year level are shown in parentheses.

Fifth, we replace the host region × year fixed effects with host country × year fixed effects. These more granular fixed effects force the PPML estimator to drop nearly half of our initial observations (up to 10,416) due to the well-known separation problem in the presence of high-dimensional fixed effects (Correia et al., 2020). Despite fewer observations, our baseline results for military-related lending still hold. Indeed, as we show in Table G.III, our main coefficient of interest on $Foreign \times Conflict \times Military$ (β_3) remains robust to this switching, preserving its magnitude and high statistical significance. The coefficient on $Foreign \times Conflict$ (β_1), in turn, loses significance with host country × year fixed effects. This arises because granular fixed effects absorb much of the variation in general

Table G.III. Aggregate-level analysis: More granular fixed effects

		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	0.208	-0.228
		(0.356)	(0.365)	(0.365)	(0.234)
Foreign × Military	β_2		-0.184***		
			(0.046)		
Foreign × Conflict × Military	β_3		1.679***	1.680***	1.623***
			(0.389)	(0.390)	(0.364)
Conflict		✓	✓	✓	✓
Host country × Year FE		✓	✓	✓	✓
Conflict × Military FE			✓	✓	✓
Foreign × Military FE				✓	✓
Military × Year FE				✓	✓
Foreign × Year FE				✓	✓
Foreign × Host Country					✓
N obs		12,440	12,440	12,440	12,164
N of host region × year clusters		229	229	229	229
R^2 (adj.)		0.778	0.837	0.841	0.867

Note: This table shows the results from estimating a version of Equation (7) that replaces *Host region* × *Year* fixed effects with more granular *Host country* × *Year* fixed effects. The estimation method is 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 E.I for the relevant SIC codes). *Host Region* includes the following regions: *ECA* is Europe and Central Asia, *EAP* is East Asia and Pacific; *NA* is North America, *LAC* is Latin America and the Caribbean; *MENA* is Middle East and North Africa; *SAR* is the South Asia region; *SSA* is Sub-Saharan Africa, and the rest. 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 host region × year level are shown in parentheses.

foreign lending during conflicts, leaving limited residual variation to identify the average effect across sectors. Identification of β_1 relies on within country-year comparisons of foreign versus domestic lending, but in many conflict episodes there is little remaining variation in non-military lending once such fixed effects are imposed. As discussed in Section 6.2, this is especially relevant because foreign banks' flight-home response is strongest in countries with limited prior specialization (variation largely absorbed by host country × year fixed effects). By contrast, the triple interaction (β_3) remains identifiable as it exploits cross-sectoral (military versus non-military) variation within country-year cells. Host region $\times$ year fixed effects therefore strike a balance, preserving identifying variation while controlling for regional time-varying shocks. In the loan-level analysis (Table 2), the much larger sample allows us to include host country $\times$ year fixed effects.

We next assess the robustness of our loan-level regressions. We first re-run Equation (8) while defining the variable $Conflict$ using different casualty thresholds. Recall that our baseline specification, reproduced in column (6) of Table G.IV, 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).

Table G.IV. 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)
Foreign × Conflict	0.023	0.100	0.133	0.031	-0.260**	-0.313***
	(0.026)	(0.076)	(0.143)	(0.134)	(0.104)	(0.116)
Foreign × Military × Conflict	0.073***	0.117***	0.433***	0.563***	0.409***	0.523***
	(0.028)	(0.041)	(0.093)	(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.)	0.867	0.867	0.867	0.867	0.867	0.867

Note: This table reports estimates of Equation (8) with the natural logarithm of the loan amount as the dependent variable. *Foreign* equals one if the bank lends to a firm located abroad, and *Military* equals one if the borrower operates in a primary or dual-use military-related SIC sector (see Table E.I). The *Conflict* indicator is one if the firm's country experiences > 100, 250, 500, 750, or 1,000 battle-related deaths in a given year. All regressions include the specified fixed effects. Data sources are UCDP and DealScan. Standard errors are clustered by bank (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We find no difference in the response of domestic and foreign bank 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 Table G.IV. The estimates reported in Table G.IV 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 conflict.

Second, in Table G.V, 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 G.IV, 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.

Table G.V. 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***	-0.027***	-0.112***	-0.116***	-0.037*	0.314
	(0.000)	(0.007)	(0.020)	(0.016)	(0.021)	(0.275)
Foreign × Conflict × Military	0.000***	0.023***	0.065***	0.080***	0.059***	0.067***
	(0.000)	(0.007)	(0.014)	(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.)	0.867	0.867	0.867	0.867	0.867	0.867

Note: Estimates from Equation (8) with log loan amount as the dependent variable. *Conflict* is measured as continuous battlefield deaths above threshold j; values below j are coded as zero. *Foreign* equals one for cross-border lending. *Military* identifies military-related SIC sectors (Table E.I). Data: UCDP and DealScan. All regressions include fixed effects as specified. ***, **, * indicate significance at 1%, 5%, and 10%. Standard errors clustered by bank are shown in parentheses.

Third, in Table G.VI, 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 E.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.

Table G.VI. Different military sector classifications

	Dependent variable: $Loan_{bft}$				
	Primary & dual-use	Dual-use only	Primary-use only	AI only	HS6 approach
	(1)	(2)	(3)	(4)	(5)
Foreign × Conflict	-0.313***	-0.317***	-0.268**	-0.313**	-0.317***
	(0.116)	(0.117)	(0.116)	(0.125)	(0.119)
Foreign × Conflict × Military	0.523***	0.498***	0.379*	0.450***	0.317***
	(0.105)	(0.106)	(0.212)	(0.097)	(0.090)
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	1,303,922	1,086,755	1,308,048	1,308,048
N of banks	14,021	14,021	13,166	14,021	14,021
R^2 (adj.)	0.867	0.867	0.866	0.867	0.867

Note: This table shows the results from estimating Equation (8). 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 either in a primary or a dual-use military-related SIC sector (see Table E.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 a dual-use SIC sector. In column (3), *Military* is a dummy equal to one if the loan is extended to a firm operating in a primary military-related SIC sector. In column (4), we use an AI-only approach without relying on an export control list. In column (5), we draw on the subsample of military and dual-use HS6 products from Chupilkin et al. (2023). All regressions include 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 are shown in parentheses.

Additionally, we implement two alternative classifications of military-related 4-digit SIC codes. First, instead of mapping the UK Export Control List via ChatGPT, we prompt the model in an unstructured manner to identify SIC codes plausibly related to the military sector without external references. Using the codes flagged by the model, the results remain similar (Table G.VI, column (4)). Second, we follow Chupilkin et al. (2023), using their list of military and dual-use HS6 products subject to EU/UK sanctions, and link these to SIC codes via the HS6–SIC concordance of Pierce and Schott (2012). A 4-digit SIC code is classified as military or dual-use if it contains at least one sanctioned HS6 product. Results are again stable under this approach (Table G.VI, column (5)).

Fourth, in Table G.VII, we perform several robustness tests related to missing loan shares and the heterogeneity of syndicates and loan types.

Table G.VII. 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	-0.313***	-0.164**	-0.367***	-0.294**	-0.339***	-0.327***
	(0.116)	(0.066)	(0.120)	(0.115)	(0.125)	(0.120)
Foreign × Conflict × Military	0.523***	0.489***	0.502***	0.439***	0.556***	0.567***
	(0.105)	(0.084)	(0.126)	(0.108)	(0.104)	(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	1,307,102	1,177,191	1,267,037	899,699	1,201,935
N of banks	14,021	14,013	13,729	13,958	10,931	13,639
R^2 (adj.)	0.867	0.886	0.871	0.868	0.893	0.876

Note: The table shows the results from estimating Equation (8) 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 E.I for the relevant SIC codes). All regressions include 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 are shown in parentheses.

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)) and 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.

Fifth, in Table G.VIII, we check whether our results are not driven by a handful of source countries. We exclude large and important countries, both economically and in terms of overall number of creditors. This confirms that our results are not driven by specific countries.

Table G.VIII. Excluding foreign banks from major economies

Dependent variable	$Loan_{bft}$					
Excl. banks from	US	Japan	DE	FR	UK	China
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.320***	-0.304**	-0.305***	-0.315***	-0.346***	-0.323***
	(0.118)	(0.118)	(0.117)	(0.119)	(0.120)	(0.118)
Foreign × Conflict × Military	0.553***	0.531***	0.494***	0.520***	0.610***	0.542***
	(0.113)	(0.108)	(0.107)	(0.109)	(0.099)	(0.108)
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	872,877	1,104,600	1,224,094	1,227,107	1,229,754	1,271,767
N of banks	9,399	12,681	13,361	13,459	13,573	13,105
R^2 (adj.)	0.889	0.763	0.871	0.870	0.871	0.868

Note: The table shows the results after excluding major economies in our dataset. We exclude banks from the US, Japan, Germany, France, China, and the UK in columns (1), (2), (3), (4), (5), and (6), 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 E.I for the relevant SIC codes). All regressions include 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 are shown in parentheses.

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%, column (4)); China (2.7%, column (5)); and the UK (6%, column (6)).

Finally, Table G.IX shows results for restricted lender samples. Column (2) limits the sample to the 575 largest global syndicated lenders (>300 loan tranches), confirming that results are not driven by small lenders. Column (3) isolates cross-border lending by excluding affiliate-based loans, with the coefficient slightly larger and still significant at 1%.

Table G.IX. Different subsamples of lenders

Dependent variable	$Loan_{bfsct}$		
	Baseline	Largest lenders	Without foreign affiliates
	(1)	(2)	(3)
Foreign × Conflict	-0.313***	-0.532***	-0.354***
	(0.116)	(0.191)	(0.135)
Foreign × Conflict × Military	0.523***	0.410**	0.605***
	(0.105)	(0.159)	(0.121)
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	980,396	1,171,502
N of banks	14,021	575	10,584
R^2 (adj.)	0.867	0.878	0.881

Note: This table reports estimates of Equation (8) for two restricted samples: the 575 largest global syndicated lenders (column (2)) and foreign banks' headquarters only (column (3)). The dependent variable is the natural logarithm of the loan amount. *Foreign* equals one if the bank lends abroad, *Conflict* equals one if the firm's country had over 1,000 battle-related deaths in a year, and *Military* equals one if the loan is to a military-related SIC sector (Table E.I). Regressions include the specified fixed effects. Data are from UCDP and DealScan. Standard errors are clustered by bank. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Appendix H Real effects of cross-border lending: additional results

Table H.I. Firm performance during violent conflicts: 2SLS estimates using a wider pre-conflict window

Dependent variable	Debt	Tangible Assets	Debt	Revenue	Debt	Employment
	1st-stage	*2nd-stage*	*1st-stage*	*2nd-stage*	*1st-stage*	*2nd-stage*
	(1)	(2)	(3)	(4)	(5)	(6)
Borrowing (0/1)	4.288***		4.288***		4.505***	
	(0.580)		(0.580)		(1.202)	
Foreign share	-1.226*		-1.226*		-1.650	
	(0.756)		(0.756)		(1.323)	
Foreign share × Military	3.901***		3.901***		4.423***	
	(0.907)		(0.907)		(0.958)	
Debt (*predicted*)		1.277***		1.357***		0.652***
		(0.122)		(0.190)		(0.107)
Host Country × Military × Year FE	✓	✓	✓	✓	✓	✓
N obs	3,374	3,374	3,374	3,374	842	842
N conflicting countries	12	12	12	12	11	11
N of military firms	268	268	268	268	74	74
N of civilian firms	2,903	2,903	2,903	2,903	702	702
SD of Foreign share ($Military = 0$)	0.112		0.112		0.182	
SD of Foreign share ($Military = 1$)	0.156		0.156		0.236	
First-stage F-statistic	84.31		84.31		78.55	
P-value of Hansen's J-test		0.203		0.080		0.591

Note: This table presents 2SLS estimates of equations (11) and (12). The first-stage dependent variable is log total long-term debt (*Debt*, columns 1, 3, 5); second-stage outcomes are the logs of tangible assets (col. 2), revenues (col. 4), and employment (col. 6). All variables are averaged over the first three conflict years ($t \in [t^*, t^* + 3]$). *Borrowing* (0/1) indicates credit from any bank during $t^* - 4$ to $t^* - 2$; we exclude $t^* - 1$ to mitigate pre-trends (Figure 2). $Foreign\,share$ measures pre-conflict exposure to cross-border lenders over the same period (Eq. 10). All other notations follow Table 4. Regressions include specified fixed effects and use inverse firm revenues as weights to emphasize credit-constrained firms. First-stage F-statistics are Kleibergen-Paap rk Wald. Data are from UCDP, DealScan, and Compustat. Standard errors (in parentheses) are clustered by country × sector. ***, **, * denote significance at the 1%, 5%, and 10% levels.

Appendix I Composition of country dyads

Table I.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		Canada	Nigeria	Czech Republic	Iraq
Canada		Croatia	Pakistan	France	Nigeria
Croatia		Czech Republic	Philippines	Germany	Pakistan
Czech Republic		Denmark	Russia	Italy	Philippines
Denmark		Finland	Sri Lanka	Japan	Sri Lanka
Finland		France	Türkiye	Netherlands	
France		Germany		Portugal	
Germany		Greece		Spain	
Greece		Hungary		Sweden	
Ireland		Iceland		Switzerland	
Israel		Israel		United Kingdom	
Italy		Italy		United States	
Japan		Japan			
Malta		Liechtenstein			
Netherlands		Luxembourg			
Norway		Netherlands			
Poland		Norway			
Portugal		Poland			
Slovakia		Portugal			
South Korea		Russia			
Spain		Slovakia			
Sweden		South Korea			
Switzerland		Slovenia			
United Kingdom		Spain			
United States		Sweden			
		Switzerland			
		United Kingdom			
		United States			
29	4	32	10	16	9

Table I.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	Russia	Angola	Angola	Australia	Colombia
Austria	Türkiye	Argentina	Colombia	Austria	Congo, DR
Bahrain	Ukraine	Australia	Congo, DR	Brazil	India
China		Austria	India	China	Nigeria
India		Azerbaijan	Iraq	Ghana	Pakistan
Japan		Bahrain	Nigeria	India	Sri Lanka
Jordan		Bangladesh	Pakistan	Ivory Coast	
Kuwait		Brazil	Philippines	Japan	
Mauritius		Chile	Russia	Kuwait	
Pakistan		China	Sri Lanka	Lebanon	
Qatar		Ghana	Turkey	Philippines	
Russia		India		Singapore	
Saudi Arabia		Ireland		South Africa	
Singapore		Ivory Coast		South Korea	
South Africa		Japan		Togo	
South Korea		Jordan		UAE	
UAE		Kazakhstan			
		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	3	40	11	16	6

Table I.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	Russia	Bahrain	Angola	Afghanistan	Algeria
Egypt	Türkiye	Brunei	Colombia	Bahrain	Colombia
India	Ukraine	China	Congo, DR	Brunei	Congo, DR
Indonesia		Egypt	India	China	India
Lebanon		India	Iraq	Egypt	Iraq
Oman		Indonesia	Nigeria	India	Nigeria
Tunisia		Iran	Pakistan	Indonesia	Pakistan
		Jordan	Philippines	Jordan	Philippines
		Kuwait	Russia	Kuwait	Sri Lanka
		Lebanon	Sri Lanka	Lebanon	
		Malaysia	Türkiye	Oman	
		Morocco		Pakistan	
		Oman		Philippines	
		Pakistan		Qatar	
		Qatar		Thailand	
		Saudi Arabia		UAE	
		Sri Lanka		Venezuela	
		Thailand			
		Tunisia			
		UAE			
7	3	20	11	17	9