

Violent Conflict and Cross-Border Lending*

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Abstract

War changes whom cross-border lenders finance. Using syndicated loan data (1989–2020), we show that violent conflict triggers a sectoral reallocation rather than a uniform retreat. Relative to domestic banks, cross-border lenders roughly halve lending to civilian firms but more than double lending to military and dual-use firms, at longer maturities. The civilian cut is supply-driven, whereas the military expansion accommodates demand that impaired domestic banks cannot meet. Unlike official war lending, this expansion does not follow alliances: it follows unmet demand across geopolitical blocs. Military firms with more pre-conflict cross-border borrowing grow faster during conflicts, while similarly exposed civilian firms grow more slowly.

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1 Introduction

Over the past 15 years, the number of state-based armed conflicts has more than doubled, from 31 in 2010 to 65 in 2025, the highest level since 1946 (Davies, Pettersson and Öberg, 2026). Beyond their human toll, these conflicts disrupt economic activity and create substantial public and private funding needs. Prior work shows that states finance wars through taxation, public debt, and official credit from allies (Gennaioli and Voth, 2015; Zielinski, 2016; Horn, Reinhart and Trebesch, 2026). Yet governments are not the only wartime borrowers: defense-related firms rely heavily on credit, much of it from private lenders.¹ While we know that private creditors pull back from sovereign lending during wars (Horn et al., 2026), we know little about their lending to firms. Do they retreat across the board or re-allocate credit toward the war effort? Using global syndicated loan data, we find that the answer depends on who lends. Relative to domestic banks, cross-border lenders cut credit to civilian firms in conflict countries by about half but more than double lending to military and dual-use firms, at longer maturities.

This reallocation runs counter to the “flight home” effect, the tendency of cross-border lenders to retrench when funding tightens or host economies suffer shocks (Giannetti and Laeven, 2012; Broner, Didier, Erce and Schmukler, 2013; De Haas and Van Horen, 2013). Applied to war, this logic predicts a broad retreat, since conflict damages firms’ assets and erodes their ability to pledge collateral (Shpak, Earle, Gehlbach and Panga, 2023; Benmelech and Monteiro, 2025b). But war differs from many other adverse shocks in two ways. First, it hits firm collateral and domestic bank capital simultaneously. In the framework of Morgan, Rime and Strahan (2004), which we adapt to guide our tests, cross-border lenders amplify collateral shocks but cushion bank capital shocks, so the two shocks have offsetting effects on lending. Second, war affects sectors unevenly, lowering the pledgeable income of civilian firms but raising that of military firms. Together, these features predict reallocation rather than retreat. Because cross-border lenders can redeploy capital abroad, they should cut credit to civilian firms by more than domestic banks do, amplifying the collateral shock. Military firms, by contrast, become more creditworthy just as domestic banks lose lending capacity, so cross-border lenders step in. This substitution should be stronger where domestic banking

¹Longo, Meggiolaro and Felipe (2024) estimate that financial institutions provided \$1 trillion to the global defense industry during 2020–2022 alone.

is shallower.

To test these predictions, we use DealScan data on 1.3 million loan shares extended by 14,021 lenders to 97,169 firms across 179 countries between 1989 and 2020. Syndicated loans account for almost three-quarters of cross-border credit flows (Doerr and Schaz, 2021), making them a key component of international lending. We merge these data with the Uppsala Conflict Data Program (UCDP) and define conflict years as those in which state-based armed conflicts cause at least 1,000 battle-related deaths; 38 countries experience at least one such year (Figure 1). Using the UK Strategic Export Control Lists and a large language model, we then identify 10 primary military and 79 dual-use industries, which together account for 17% of syndicated lending in our sample.

We first analyze a country-year panel comparing cross-border and domestic lending to military and civilian firms. During conflicts, cross-border lending to civilian firms falls by about half relative to domestic banks, while lending to military firms more than doubles. Event studies show that both patterns emerge only after conflict onset. We then turn to loan-level data, where we compare lending decisions by individual banks to firms within the same host country and year. Our design does not require violent conflict to be randomly assigned: host country $\times$ year fixed effects absorb country-year-specific determinants of conflict and aggregate credit demand. Identification therefore requires only that, absent conflict, cross-border and domestic lending to military and civilian firms would have evolved similarly, which event studies support. This comparison confirms the reallocation within host country-years: cross-border lending to civilian firms falls by 27% relative to domestic banks, lending to military firms does not fall, and the difference between the two is significant at the 1% level throughout. Cross-border lenders also extend military loans at maturities that are 12% longer. The military expansion does not spill over to neighboring countries and does not outlast the fighting for long, reversing in the third year after hostilities end.

We next examine whether the reallocation reflects lender supply or borrower demand. Following Khwaja and Mian (2008), we hold credit demand fixed with host country $\times$ military $\times$ year fixed effects, which absorb demand for military and civilian firms separately within each country-year. Alternatively, we hold credit supply fixed with bank $\times$ industry $\times$ year fixed effects, which absorb each bank’s industry-specific lending capacity in a given year. The civilian retrenchment survives when demand is held fixed but is no longer significant when we fix supply, consistent with a cut in lenders’ credit supply. The military reallocation does

the opposite: it survives when supply is held fixed but is no longer significant when we fix demand, consistent with cross-border lenders accommodating wartime credit demand rather than shifting their own credit supply toward defense borrowers.

Three further pieces of evidence support the view that cross-border lenders meet wartime credit demand that domestic banks cannot. First, panel local projections (Jordà and Taylor, 2016) using Compustat data on nearly 84,000 listed firms in 124 countries show that military firms’ revenues rise by 11% relative to civilian firms in a conflict year and by 20% four years later. This pattern is consistent with higher pledgeable income among military firms. Second, relative to matched peaceful countries, real deposits in domestic banking systems fall by about 10% in the conflict year and 25% one year after onset, limiting domestic banks’ ability to meet wartime credit demand. Third, the reallocation toward the military sector is larger where domestic banking systems are shallow.

Next, we ask which lenders expand credit to military firms during violent conflicts. Lenders may finance the defense sectors of geopolitically aligned countries (*alliance finance*, the private analogue of the official war lending documented by Horn et al. (2026)), go wherever wartime demand is unmet (*arm’s-length finance*), or finance politically distant countries, where financing war carries lower reputational and political costs at home (*outsider finance*). Military lending should then rise only within blocs, both within and across blocs, or only across blocs. We assign countries to geopolitical blocs using UN General Assembly votes (Bailey, Strezhnev and Voeten, 2017) and formal alliances, and compare lenders from different blocs that lend to the same conflict country.

We find that lenders from every bloc cut civilian lending during conflicts and shift their lending toward military firms. Military lending itself, however, expands across blocs but not within them. Western and Neutral lenders expand military lending to Eastern conflict countries, whereas Western lenders cut military lending to Western conflict countries, and NATO and BRICS lenders do not expand it to fellow members. State-owned and private lenders behave alike, which is inconsistent with state direction. This dyadic pattern fits both outsider and arm’s-length finance. A direct test helps to separate the two views: once we compare aligned and non-aligned lenders within the same conflict country, sector, and year, they respond identically. This rules out a lender-side alignment effect large enough to explain the cross-bloc pattern. The evidence therefore favors arm’s-length finance: the cross-bloc expansion in military lending reflects where unmet wartime demand arises, not

lender-side political preferences.

We end the paper by examining whether the credit reallocation matters for firms. Using Compustat data, we relate firm outcomes during conflict to their pre-conflict exposure to cross-border lenders, measured as the cross-border share of a firm’s syndicated borrowing. Because host country $\times$ military status $\times$ first conflict year fixed effects absorb the wartime demand shock, we compare military (civilian) firms in the same country that differ in this exposure. Among civilian firms, a 10 percentage-point higher exposure is associated with 8% lower liabilities and 4–5% lower assets and revenues during the conflict. Among military firms, it is associated with 15% *more* assets and 13% higher revenues. In a placebo test on earlier pre-conflict outcomes, exposure predicts none of these outcomes for either group, although the military–civilian gap is already significant for revenues. This pattern is consistent with wartime demand translating into stronger outcomes mainly for military firms with more pre-conflict exposure to cross-border lenders, as expected if domestic banks cannot fully meet credit demand. Because these estimates are conditional associations and rest on a relatively small sample of military firms, we interpret them as descriptive.

Related literature. Our paper speaks to three strands of the literature. First, we contribute to work on the international transmission of shocks through cross-border lending.² Cross-border lenders typically retrench more sharply than domestic banks after adverse local shocks. Because this literature mostly estimates average effects, it leaves open whether the retrenchment reflects an indiscriminate withdrawal or a reallocation toward higher returns. Violent conflict separates the two: within the same country and year, it lowers the pledgeable income of civilian firms and raises that of military ones. We show that cross-border lenders retrench where pledgeable income falls and stay, or expand, where it rises. Whether they stabilize or destabilize a host economy therefore depends on the sectoral composition of local shocks, and aggregate flight-home estimates may mask large differences across industries.

²See, among others, Chava and Purnanandam (2011), Cetorelli and Goldberg (2011), Giannetti and Laeven (2012), Popov and Udell (2012), Schnabl (2012), De Haas and Van Horen (2012, 2013), Cerutti, Hale and Minoiu (2015), Paravisini, Rappoport, Schnabl and Wolfenzon (2015), and Doerr and Schaz (2021) on financial crises; Popov and Van Horen (2015) and Acharya, Eisert, Eufinger and Hirsch (2018) on shocks to risky assets; Bräuning and Ivashina (2020), Cetorelli and Goldberg (2012), and Correa, Paligorova, Saprizza and Zlate (2022) on monetary policy; Aiyar, Calomiris, Hooley, Korniyenko and Wieladek (2014), Tripathy (2020), and Borchert, De Haas, Kirschenmann and Schultz (2026) on regulatory changes; and Alfaro, Brussevich, Minoiu and Presbitero (2025) on trade disruptions.

Second, we contribute to recent research on financial markets and military conflict. Prior work focuses on sovereign borrowing: Horn et al. (2026) show that official creditors step in during great-power wars, when private creditors stop lending to states. We show that private lenders do not simply retreat from corporate lending. Our evidence therefore suggests that war finance has two tracks: sovereigns rely on official credit from allies (Horn et al., 2026), while military-related firms turn to private cross-border credit, especially when domestic banks are impaired (Benmelech and Monteiro, 2025b).³

Third, we shed light on the financial dimensions of geopolitical fragmentation. In the real economy, trade, investment, and supply chains increasingly fragment along geopolitical lines (Alfaro and Chor, 2023; Gopinath, Gourinchas, Presbitero and Topalova, 2025).⁴ In financial markets, U.S. banks have responded to heightened geopolitical risk by reducing cross-border lending while maintaining credit through local affiliates (Niepmann and Shen, 2025). In peacetime, political alignment with foreign governments shapes institutional investors' cross-border capital allocation (Kempf, Luo, Schäfer and Tsoutsoura, 2023). We show that wartime military credit does not follow political alignment: cross-border lenders expand military lending in conflict countries outside their own bloc, and aligned and non-aligned lenders respond alike once the destination is held fixed.

We proceed as follows. Section 2 presents the conceptual framework and its predictions, Section 3 our data, and Section 4 the empirical strategy. Section 5 reports our main results, while Section 6 separates lender supply from borrower demand. Section 7 examines geopolitical alignment. Section 8 then turns to firm outcomes, after which Section 9 concludes.

³Related work examines the macro- and microeconomic effects of war. At the macro level, studies estimate the economic costs of war (Glick and Taylor, 2010; Federle, Meier, Müller, Mutschler and Schularick, 2026) and how military spending shapes conflict and its outcomes (Benmelech and Monteiro, 2025a; 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; Fisman, Sarkar, Skrastins and Vig, 2020; Korovkin and Makarin, 2023; Mishra and Ongena, 2020).

⁴See also Chupilkin, Javorcik and Plekhanov (2026) on connector countries and trade rerouting. Related work on sanctions shows that banks can circumvent restrictions by lending through less-regulated foreign affiliates (Besedeš, Goldbach and Nitsch, 2017; Efung, Goldbach and Nitsch, 2023).

2 Conceptual framework

We draw on the framework of Morgan et al. (2004) for capital allocation by integrated financial intermediaries, which extends Holmström and Tirole (1997) to multi-market settings. In this framework, integrated banks allocate capital toward locations offering the highest risk-adjusted returns. In doing so, they cushion location-specific shocks to bank capital but amplify demand or collateral shocks.

Financial integration and credit reallocation. To fix ideas, consider two countries indexed by $j \in \{H, F\}$. Cross-border lenders are headquartered in the home country H . Borrowers are located in the foreign country F , which may be affected by violent conflict, and banks headquartered in F are domestic lenders. Let A_j denote the aggregate pledgeable income of firms in country j , including the value of their collateral. It determines the maximum expected return that borrowers can credibly promise to lenders. The return to bank capital deployed in country j can be represented as

$$R_j = g(A_j, K_j), \quad (1)$$

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

With financial integration, bank capital moves across borders to equalize risk-adjusted returns:

$$R_H = R_F = R^*. \quad (2)$$

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 shocks. Violent conflict hits the borrower country in two ways. First, it involves a severe negative shock to the expected return on lending. Conflict raises macroeconomic uncertainty, weakens contract enforcement, destroys physical collateral, and increases the probability of expropriation. In the language of Morgan et al.

(2004), this corresponds to a negative collateral shock in country F : the income that firms can credibly promise to lenders declines, reducing the return to bank capital deployed there.

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

$$A_F \rightarrow A_F - \Delta. \quad (3)$$

This shock lowers R_F below R_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 $R^{*'} < R^*$. 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 their home market.

Second, conflict impairs the domestic banking system itself. Physical damage, deposit withdrawals, and losses on sovereign and corporate exposures erode the capital and funding base of banks located in the conflict country. Section 6.3 documents the resulting declines in deposits and loans and the rise in non-performing loans. Let $K_F = K_F^d + K_F^x$ denote bank capital in country F , supplied by domestic (d) and cross-border (x) lenders. Conflict reduces domestic capital by $\Gamma > 0$:

$$K_F^d \rightarrow K_F^d - \Gamma. \quad (4)$$

Because R_F is decreasing in K_F , this shock raises the return to lending in F and draws integrated capital in. Financial integration thus amplifies collateral shocks but cushions shocks to local bank capital. Domestic lenders, whose funding is tied to the local deposit base, cannot draw on outside capital to offset their losses, but cross-border lenders can.

The military sector and sector-specific return shocks. Because conflict affects sectors in opposite directions, we extend the framework to allow for sector-specific pledgeable income. For civilian firms, conflict reduces demand as household incomes fall and public spending shifts toward defense, and it disrupts supply chains and labor supply through mobilization and displacement, lowering pledgeable income. For military firms, government procurement contracts and wartime demand raise expected profitability, raising pledgeable income.

Let $s \in \{c, m\}$ index civilian and military sectors, respectively, with sectoral pledgeable

income A_j^s and return $R_j^s = g(A_j^s, K_j^s)$, where $A_j = A_j^c + A_j^m$. Conflict affects pledgeable income asymmetrically across sectors in the foreign country:

$$\frac{\partial A_F^c}{\partial \text{Conflict}} < 0 \quad \text{and} \quad \frac{\partial A_F^m}{\partial \text{Conflict}} > 0. \quad (5)$$

The first inequality captures the destruction of civilian collateral values while the second reflects the enhanced profitability and implicit government support enjoyed by military-related firms during wartime. The aggregate shock Δ in equation (3) is thus the net decline, with civilian losses outweighing military gains. These opposing forces generate within-country heterogeneity in returns at pre-conflict capital allocations:

$$R_F^m > R^* > R_F^c. \quad (6)$$

International lenders can arbitrage such sectoral return differentials because they draw on capital from other markets. Domestic lenders face the same incentive but can reallocate only a capital base that conflict has reduced by Γ . They cannot replace this capital with outside funding during the conflict, and the rise in military pledgeable income is large relative to what remains. Even shifting all of it toward military firms would not meet the increase in military credit demand. Cross-border lenders face neither constraint. Capital therefore follows pledgeable income: integrated lenders withdraw from civilian lending in the conflict country and expand military lending there until returns equalize across country–sector pairs.

When we combine the two shocks, the collateral shock dominates in the civilian sector as long as the loss of civilian pledgeable income is large relative to the loss of domestic bank capital. Cross-border lenders, who have an outside option, withdraw while domestic lenders, who do not, remain exposed. In the military sector, by contrast, the two shocks reinforce each other: rising pledgeable income raises the return to lending, and impaired domestic banks leave part of the resulting demand unmet for cross-border lenders to fill. Conflict should therefore shift the financing of military firms from domestic to cross-border lenders.

Testable predictions. The framework yields three predictions:

Prediction 1

Cross-border lenders reduce lending to civilian firms in conflict countries by more than

domestic lenders do. Because this gap reflects the lenders' different outside options rather than differences in borrower demand, it should persist when country-sector credit demand is held fixed but attenuate when each lender's sector-specific supply is held fixed.

Prediction 2

Cross-border lenders increase lending to military firms in conflict countries by more than domestic lenders do. Because this gap reflects higher credit demand by military firms that impaired domestic banks cannot meet, it should persist when each lender's sector-specific supply is held fixed. Because the supply difference between lender types is common to both sectors, however, the military gap should converge to the civilian gap when country-sector credit demand is held fixed.

Prediction 3

The relative expansion of cross-border military lending is larger in countries with shallow banking systems, where the domestic capital base is small relative to the rise in military firms' pledgeable income.

3 Data

3.1 Data sources and sample

We rely on three main data sources. The first is the Uppsala Conflict Data Program (UCDP), which 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 assign battle deaths to the country where the fighting takes place and aggregate them at the country-year level. Figure 1 shows that 38 countries experienced at least one year with at least 1,000 battle-related deaths (Internet Appendix (IA) Table IA.1

lists them).⁵ Almost all conflicts in the sample with at least 1,000 annual battle-related deaths are intrastate, although 21% also involve interstate hostilities.

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, industries, 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%.⁶ 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.⁷

Our sample includes 1,324,617 bank–firm–year observations, corresponding to 861,437 distinct bank–firm relationships, 14,021 unique creditors, and 97,169 unique borrowers.⁸ Cross-border loans account for 47% of observations. Appendix Table A.I defines the variables, and Appendix Table B.I reports summary statistics.

Third, we use Compustat to test whether conflict raises the profitability of military firms (Section 6.2) and to relate firm outcomes to pre-conflict exposure to cross-border lenders (Section 8). The sample covers 70,533 civilian and 13,439 military firms across 124 countries (1,068,807 firm-year observations). We assign firms to primary military, dual-use, and civilian industries using the same four-digit SIC classification as for the DealScan borrowers.

⁵Of these, 16 borrow in the syndicated loan market and enter our loan-level analysis (while the other 22 enter the aggregate country-year analysis with zero borrowing). In these 16 countries, foreign syndicated loan originations in DealScan total \$0.83 trillion over 1989–2020, against \$2.18 trillion of gross external commercial-bank disbursements in the World Bank International Debt Statistics for the same matched borrower-country years, or roughly 38%. The share is 53% in conflict years and 35% outside conflict years.

⁶Results are robust to alternative imputation methods, including equal splits across syndicate members (De Haas and Van Horen, 2013). See Table IA.8.

⁷Results are robust to restricting the sample to loans provided by banks’ headquarters. See Table IA.10.

⁸We exclude banks issuing only one loan, reducing the number of creditors from about 21,000 to 14,021.

3.2 Identifying military and dual-use industries

We distinguish between lending to firms in the military and the civilian sector. The military sector comprises primary military and dual-use industries; all other industries are civilian.⁹ Primary military industries produce goods predominantly for defense purposes, such as missiles and tanks. Dual-use industries, by contrast, produce civilian goods or technologies with clear military applications. For example, commercial aircraft engine technologies can be readily adapted for fighter jets, whose engines rely on similar materials and propulsion systems.

In the absence of an established classification separating civilian, primary military, and dual-use industries, 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 four-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 modified version of the same approach. We extract keywords from UK dual-use category titles (e.g., nuclear, marine) and search for these terms in NAICS and SIC classifications, yielding 114 candidate dual-use SIC codes. We then score each of the 124 codes (10 primary military and 114 dual-use) for military relevance using a large language model (GPT-4o), which assesses the likelihood that an industry’s output has military applications. We repeat the scoring 50 times with randomly ordered SIC codes and average the likelihoods across runs (see Internet Appendix A.2). Rank orders are highly consistent across runs (Figure IA.1), and the model assigns average likelihoods of 95–100% to all primary military industries, which we include as an unlabeled validation check. We retain the 10 primary military industries and 79 dual-use industries with an average likelihood

⁹Throughout, we use “industry” for SIC-based classifications and “sector” for the distinction between military and civilian firms.

above 50%, which together account for about 17% of total syndicated lending volume.^{10,11}

The resulting group is dominated by dual-use industries, which account for 16.8% of loan observations, against 0.3% for primary military industries. By loan count, the largest dual-use industries are telecommunications services (SIC 4812, 4813, and 4899), industrial chemicals, electronic components, semiconductors, engineering services, software, and steel (Table IA.2). This composition reflects how modern armed forces are supplied: export-control lists cover these goods precisely because militaries procure them. Because broad dual-use categories may nonetheless capture civilian demand, Section 5.2.3 shows that our results hold under narrower and independently constructed definitions.

The United Kingdom, the United States, and Germany are the largest sources of syndicated lending to military firms in conflict countries, alongside Singapore, China, and the UAE (Figure IA.2). One example is a syndicated facility extended to Russia’s Severstal during the Second Chechen War. Although Severstal is primarily a commercial steel producer, it has strong ties to Russia’s defense sector: the company has supplied armored and specialized steel grades to defense enterprises since the late 1990s. In 2000 it became the formal patron of the strategic nuclear submarine TK-20, subsequently renamed *Severstal*.

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 assess whether conflict-induced shifts in cross-border lending are economically significant at the level of the aggregate economy, and to compare

¹⁰Table IA.2, Panels A and B, list the SIC codes for the primary military and dual-use industries, 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-authorisation>.

¹¹To evaluate temporal variation in export-control classifications, we compare the UK Strategic Export Control Lists from 2014 and 2024. The Military List exhibits strong textual and structural continuity across versions (TF-IDF cosine similarity: 0.91). The Dual-Use List retains the same Annex I category headings, with revisions concentrated at the level of technical sub-items. Export-control regimes are cumulative in the sense that technologies classified as militarily relevant typically remain covered in subsequent revisions. Accordingly, using the most recent consolidated list provides a consistent classification across the sample period, and any residual differences do not materially affect our empirical results.

them with shifts in domestic bank lending. We aggregate all bank-firm-year observations to the lender origin country-sector-year level, where “lender origin” distinguishes cross-border from domestic lenders, “country” denotes the borrower’s location, and “sector” distinguishes military from civilian firms. We include zeros for lender origin country-sector-year cells without lending, creating a balanced panel that captures both the intensive and extensive margins of lending. We then estimate the following regression equation:

$$\begin{aligned} Loan_{gsct} = \exp & \left[\beta_0 \cdot Foreign_{gc} + \beta_1 \cdot Foreign_{gc} \times Conflict_{ct} \right. \\ & + \beta_2 \cdot Foreign_{gc} \times Military_s \\ & + \beta_3 \cdot Foreign_{gc} \times Conflict_{ct} \times Military_s \\ & \left. + \eta_{rt} + \gamma_{vs} + \delta_{gs} + \chi_{st} + \phi_{gt} + \kappa_{gc} \right] \times \varepsilon_{gsct}, \end{aligned} \quad (7)$$

where $Loan_{gsct}$ is the total loan amount (in USD) by lender origin g to sector s in country c in year t . Because the dependent variable contains many zeros, we estimate equation (7) by Poisson pseudo-maximum likelihood (PPML) (Santos Silva and Tenreyro, 2006; Cohn, Liu and Wardlaw, 2022), using the high-dimensional fixed-effects implementation of Correia, Guimaraes and Zylkin (2020). $Foreign_{gc}$ is a dummy equal to one (zero) for cross-border (domestic) lending to country c . $Conflict_{ct}$ is a dummy equal to one if country c experiences at least 1,000 battle-related deaths in year t . $Military_s$ equals one for the military sector, which comprises firms whose primary, secondary, or tertiary SIC code appears in Table IA.2.

The specification includes the following high-dimensional fixed effects. First, η_{rt} are host region $\times$ year fixed effects that absorb all time-varying shocks common to destination countries within a region.¹² Second, γ_{vs} are conflict status $\times$ sector fixed effects, where $v \in \{0, 1\}$ indicates whether the host country is in conflict. They absorb the level effects of $Conflict_{ct}$ and $Military_s$ and their interaction (i.e., sectoral lending differences during conflicts common to both cross-border and domestic lenders). Third, δ_{gs} are lender origin $\times$ sector fixed effects that remove baseline differences between cross-border lenders and domestic banks in their propensity to lend to the military sector. Fourth, χ_{st} are sector $\times$ year fixed effects that capture time-varying aggregate shocks to military versus civilian sectors common to cross-

¹²The regions are Europe and Central Asia (ECA), East Asia and Pacific (EAP), North America (NA), Latin America and the Caribbean (LAC), Middle East and North Africa (MENA), South Asia (SAR), Sub-Saharan Africa (SSA), and a residual category comprising all other countries. Internet Appendix B discusses more granular host country $\times$ year fixed effects.

border and domestic lenders. Fifth, ϕ_{gt} are lender origin $\times$ year fixed effects that absorb aggregate time trends in cross-border versus domestic lending. Finally, κ_{gc} are lender origin $\times$ host country fixed effects that capture potential specialization of cross-border lenders in particular destination countries. Because δ_{gs} , ϕ_{gt} , and κ_{gc} each absorb $Foreign_{gc}$, and δ_{gs} also absorbs $Foreign_{gc} \times Military_s$, β_0 and β_2 are identified only in specifications without these fixed effects. We cluster standard errors by host region $\times$ year.

By construction, β_1 captures the change in cross-border relative to domestic lending to civilian firms during conflicts, and β_2 the additional cross-border–domestic gap for military firms outside conflicts. Our main coefficient of interest, β_3 , captures how much more this gap changes during conflicts for military than for civilian firms. Consistent with Section 2, we expect $\beta_1 < 0$, as cross-border lenders cut civilian credit more than domestic banks, and $\beta_3 > 0$, as they meet military credit demand that domestic banks struggle to accommodate.

Because the data are aggregated across individual lenders and firms, this specification cannot control for unobserved heterogeneity at the level of borrowers, lenders, or the home countries of cross-border lenders. We therefore use it to measure economic magnitudes, including the extensive margin, and rely on the loan-level specification below for identification within host country-years.

4.2 Loan-level analysis

At the bank-firm-year level, we estimate:

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

where $Loan_{bfsct}$ is the natural logarithm of total loans by bank b to firm f in sector s in country c (the firm’s country of incorporation) in year t . $Foreign_{bf}$ is a dummy equal to one if bank b (or its parent) and firm f are incorporated in different countries; $Conflict_{ct}$ and $Military_s$ are defined as in equation (7). We estimate equation (8) by OLS with high-dimensional fixed

effects (Correia, 2016) and cluster standard errors by lender. The coefficients have the same interpretation as in the aggregate analysis, restricted to the intensive margin, and we again expect $\beta_1 < 0$ and $\beta_3 > 0$.

Loan-level data allow us to add fixed effects that are not feasible at the aggregate level. Bank fixed effects (α_b) absorb time-invariant lender characteristics (e.g., risk appetite and business models), and firm fixed effects (θ_f) absorb time-invariant borrower heterogeneity in credit demand and creditworthiness. Bank headquarters (“home”) country $\times$ year fixed effects (μ_{ht}) and firm incorporation (“host”) country $\times$ year fixed effects (ν_{ct}) absorb shocks common to all banks or firms, respectively, in their country of incorporation in a given year. The remaining fixed effects mirror those in equation (7): conflict status $\times$ sector (γ_{vs}),¹³ lender origin $\times$ sector (δ_{gs}), lender origin $\times$ year (ϕ_{gt}), and sector $\times$ year (χ_{st}).

4.3 Identification

Violent conflict is not randomly assigned: it is more likely in poorer countries with weaker institutions, and after adverse economic shocks (Collier and Hoeffler, 2004; Miguel, Satyanath and Sergenti, 2004; Blattman and Miguel, 2010). In the loan-level specification, however, host country $\times$ year fixed effects (ν_{ct}) absorb country-level drivers of both conflict and aggregate credit demand. Hence β_1 and β_3 are identified only from how the gaps between cross-border and domestic lenders, and between military and civilian firms, change within the same country when conflict breaks out. Identification therefore requires only that, absent conflict, these gaps would have evolved similarly. We address three further concerns.

First, lenders may anticipate conflict and adjust their lending before violence escalates. The aggregate event study in Section 5.1 shows no significant pre-trends in either civilian or military lending. We also compare conflicts that break out suddenly, after a year of little violence, with conflicts that have been simmering (Internet Appendix B.2). Anticipation should matter least for sudden conflicts, yet our results are strongest there, consistent with lenders responding to realized rather than anticipated violence.

Second, cross-border lenders may select into conflict-prone countries because of political connections, risk tolerance, or expertise in military lending. Bank and firm fixed effects

¹³These fixed effects are not redundant given sector $\times$ year fixed effects (χ_{st}). Because conflict status varies across countries within a year, χ_{st} and ν_{ct} cannot absorb differences in the military–civilian lending gap between conflict and non-conflict countries.

absorb time-invariant selection, as do bank $\times$ firm fixed effects in Section 6. Time-varying selection is also unlikely to explain our results: the reallocation is no stronger among lenders that already specialized in military lending before the conflict (Section 6.3), similar for state-owned and private lenders (Section 7.3), and robust to dropping each major source country and to keeping only the most active lenders (Section 5.2.4).

Third, the loan-level sample is conditional on a loan being made. If cross-border lenders cut off some borrowers entirely, the loan-level estimates miss this exit and may partly reflect selection into surviving relationships. The aggregate specification in equation (7) addresses this: estimated on a balanced panel that includes zero-lending cells, it captures both the intensive and the extensive margin. It yields the same pattern, with larger magnitudes, and is therefore the specification from which we take the economic magnitude of both effects.

5 Main results

5.1 Aggregate results

Table 1 reports estimates of equation (7) for a balanced panel of 179 countries over 32 years. Columns (1)–(4) progressively add high-dimensional fixed effects, which absorb some lower-order terms and lead the PPML estimator to drop separated observations (Correia et al., 2020). The coefficient β_3 is stable across columns (2)–(4) and always significant at the 1% level. The civilian coefficient β_1 is positive yet insignificant in columns (1)–(2) and turns negative once column (3) adds foreign $\times$ host country fixed effects, which raise the adjusted R^2 from 0.43 to 0.82. Without these fixed effects, β_1 partly reflects the larger share of cross-border lending in countries that experience conflict. With them, it captures only the within-country change in cross-border relative to domestic lending when conflict breaks out. In our preferred specification in column (4), cross-border lenders cut civilian lending during conflicts by $e^{-0.627} - 1$, or 47%, relative to domestic banks, but expand military lending by $e^{0.947} - 1$, or about 158% ($\beta_1 + \beta_3$).¹⁴ Cross-border lenders thus expand military credit relative to domestic banks, not merely relative to their own civilian lending.

Figure 2 plots annual coefficients for β_1 (Panel A) and β_3 (Panel B) from three years before

¹⁴Although the dependent variable is in levels, the PPML exponential mean function allows coefficient estimates to be interpreted in percentage terms, as in a log-linear model.

to three years after conflict onset. Cross-border lending to civilian firms declines sharply in the three years following the outbreak of conflict, relative to domestic lending. This decline is mirrored by an immediate and sustained increase in cross-border lending to military firms relative to civilian firms over the same period. Neither pattern is present before the conflict, suggesting that the results are not driven by pre-trends.¹⁵

To further gauge economic magnitudes, we compute military-sector syndicated lending per conflict country-year, separately for cross-border and domestic lenders, and compare conflict with pre-conflict years.¹⁶ Cross-border lending to the military sector averages \$397 million per conflict country-year, up from \$330 million before onset, while domestic military lending falls from \$136 million to \$61 million. The cross-border-to-domestic ratio thus widens from 2.4 to 6.5. Scaling by the host country’s defense budget shows the same divergence: as wartime budgets expand, cross-border military credit falls from 10.3% to 4.2% of military expenditure, whereas domestic military credit almost disappears, falling from 2.1% to 0.3%. Using this measure, the cross-border-to-domestic ratio rises from about 5 to 14.

Robustness. Our results are robust to a range of alternative choices (each detailed in Internet Appendix B). First, we raise the AI-estimated military-use likelihood required to classify an industry as military-related from 50% to 90%. At 80%, only 17 industries remain: the 10 primary military industries plus aircraft, aircraft engines, aircraft parts, search and navigation systems, shipbuilding, space research, and semiconductors. Telecommunications, chemicals, steel, computers, peripherals, and software all drop out.¹⁷ Even for this core defense industrial base, the reallocation coefficient β_3 remains stable (Figure IA.3). Second, β_3 remains significant when we cluster standard errors at alternative levels (Figure IA.4). Third, the results hold under OLS with an inverse hyperbolic sine transformation of the dependent

¹⁵The statistically insignificant decline in civilian lending at $t - 1$ reflects our strict conflict definition ($\geq 1,000$ battle-related deaths). Hostilities may commence in the prior year but register fewer casualties until crossing this threshold. Section 4.3 discusses anticipation effects.

¹⁶We use up to three years before onset per episode, dropping any pre-onset year that is itself a conflict year. We include country-years with no military lending so that the averages are not conditional on positive flows. The figures cover 32 conflict episodes in 16 countries, comprising the 92 conflict country-years that appear in the loan-level sample (of the 130 listed in Table IA.1) and 76 pre-onset country-years. Military expenditure data come from the Stockholm International Peace Research Institute (SIPRI) Military Expenditure Database, which covers 91 of the 92 conflict country-years.

¹⁷An industry is retained if its average likelihood is at least the cutoff. Raising the cutoff from 80% to 90% removes only semiconductors (SIC 3674, 82.6%), leaving 16 industries. Shipbuilding (SIC 3731), at exactly 90.0%, is retained.

variable, which limits the influence of very large loan volumes (Table IA.3). Fourth, we replace host region $\times$ year with host country $\times$ year fixed effects (Table IA.4). The estimate of β_3 is virtually unchanged, and the net military effect rises to 1.331, whereas the civilian retrenchment coefficient β_1 shrinks and loses significance. While PPML drops nearly half of the observations under these fixed effects, the attenuation does not reflect the smaller sample. In the IHS-OLS specification, host country $\times$ year fixed effects leave the civilian retrenchment unchanged on the full panel, and it remains significant on exactly the sample that PPML retains (Table IA.3, column (4)). The attenuation is therefore specific to the PPML estimator under these fixed effects. The loan-level specification already includes host country $\times$ year fixed effects, and there the civilian retrenchment remains significant (Section 5.2).

5.2 Loan-level results

5.2.1 Loan amounts

Table 2 reports estimates from equation (8). As in Table 1, we progressively add fixed effects, with column (3) including all interactive fixed effects from Section 4.2. These absorb *Foreign*, *Conflict*, *Military*, *Foreign* $\times$ *Military*, and *Conflict* $\times$ *Military*, so β_0 is identified only in columns (1)–(2) and β_2 only in column (2). Despite these additional fixed effects, β_3 is essentially unchanged. In our preferred specification in column (3), cross-border lenders cut lending to civilian firms by $e^{-0.313} - 1$, or 26.9%, relative to domestic banks, but do not cut lending to military firms: the net effect is positive but imprecisely estimated ($\beta_1 + \beta_3 = 0.210$, SE 0.162). Because the loan-level sample is conditional on a loan being made, it captures the intensive margin only. The aggregate estimates in Section 5.1, which also capture the extensive margin, show that cross-border military lending expands relative to domestic banks. The loan-level data thus establish that, within the same host country and year, cross-border lenders cut civilian but not military lending relative to domestic banks, with β_3 significant at the 1% level in columns (2) and (3).

Our headline results are consistent with the conceptual framework in Section 2: conflict reallocates cross-border credit rather than triggering a uniform retreat.

5.2.2 Loan maturity

We next examine whether cross-border lenders also adjust loan maturities during conflict. We re-estimate equation (8) with two maturity outcomes as the dependent variable, keeping the right-hand side unchanged. Column (4) of Table 2 uses the log of loan maturity, and column (5) uses an indicator for loans in the upper quartile of the maturity distribution.

Cross-border lenders extend longer loans to military borrowers during conflict. Relative to domestic banks, their loan maturities to these firms rise by $e^{0.118-0.008} - 1$, or about 11.6% ($\beta_1 + \beta_3 = 0.110$, SE 0.032; column (4)). This effect comes entirely from the triple interaction: for civilian firms, the coefficient is small and insignificant. Column (5) shows a complementary pattern. Cross-border lenders become 4.4 percentage points less likely to grant long-maturity loans to civilian firms, whereas the coefficient on *Foreign* $\times$ *Conflict* $\times$ *Military* (4.9 percentage points) fully offsets this decline for military borrowers. Cross-border lenders thus shift not only loan volumes but also maturities toward military firms.

5.2.3 Alternative definitions of military industries

Because dual-use industries account for much of our military sector, the baseline estimates may capture civilian demand for communications or computing services rather than military demand. Table 3 re-estimates equation (8) under four alternative definitions (column (1) reproduces the baseline). Columns (2) and (3) split the military group into its two components, each dropping the other component from the sample. For dual-use industries alone, β_3 is 0.498 (column (2)), close to the baseline. Restricting the military group to the 10 primary military industries, for which civilian demand is limited, yields 0.379 (column (3)), about three-quarters of the baseline and less precise, as these industries account for only 0.3% of loan observations. Column (4) replaces the export-control mapping with an unstructured classification in which the language model identifies military-related SIC codes without external references. Column (5) uses no language model: following Chupilkin et al. (2026), we take the military and dual-use HS6 products subject to EU and UK sanctions, map them to SIC codes with the concordance of Pierce and Schott (2012), and classify an industry as military if it contains at least one such product. All five reallocation estimates are positive and statistically significant (column (3) at the 10% level), while the civilian retrenchment (β_1) is virtually unchanged across columns. The loan-level net military effect ($\beta_1 + \beta_3$) is

positive but insignificant under the first four definitions and zero under the sanctions-based definition. What is robust to the classification, therefore, is the loan-level reallocation of cross-border credit from civilian to military firms, and it does not depend on how broadly we define the military group or on using a large language model.

5.2.4 Robustness and extensions

We subject our loan-level results to several robustness checks, detailed in Internet Appendix C. First, β_3 is positive and significant regardless of the battle-related death threshold we use to define *Conflict* (100 to 1,000 deaths; Table IA.7). The civilian retrenchment, in contrast, appears only in relatively violent conflicts with at least 750 annual deaths. Second, both coefficients are robust when we split loan amounts equally among syndicate members, exclude loans with more than five or ten lead arrangers, keep only term loans and credit lines, or drop acquisition loans: β_1 ranges from -0.164 to -0.367 and β_3 from 0.439 to 0.567 , all significant at least at the 5% level (Table IA.8). Third, dropping banks from any one of the six largest home countries leaves both coefficients close to the baseline, with β_3 between 0.494 and 0.610 (Table IA.9). Finally, β_3 remains positive and significant when we restrict the sample to lenders participating in more than 300 loan tranches over 1989–2020 or exclude lending through foreign affiliates (Table IA.10, columns (2) and (3)).

The military expansion is also confined to countries at war and does not outlast the fighting for long (Internet Appendix Sections C.2 and C.3). Cross-border lenders do not reallocate lending toward military firms in neighboring countries that are not themselves in conflict, although they reduce civilian lending to neighbors with few or no battle-related deaths (Table IA.11). Lenders thus respond to wartime demand where it arises rather than anticipating regional escalation. After hostilities end, the cross-border lender advantage in military lending persists for two years but reverses in the third, when cross-border civilian lending begins to recover (Table IA.12).

6 Mechanism: lender supply versus borrower demand

The evidence so far indicates that violent conflicts lead cross-border lenders to shift credit toward military firms relative to domestic banks while reducing exposure to the rest of the economy. This section asks whether these effects reflect lender supply, borrower demand, or

both. Section 6.1 uses fixed effects to separate the two and finds patterns consistent with a supply-driven civilian retrenchment and a demand-driven military expansion. Section 6.2 then traces that demand to the improved performance of military firms during conflicts, and Section 6.3 explains why cross-border lenders rather than domestic banks meet it.

6.1 Disentangling credit supply and demand

To separate supply from demand, we run tests in the spirit of Khwaja and Mian (2008), exploiting two features of the syndicated loan market.¹⁸ First, banks lend to multiple firms within the same industry and year, so bank $\times$ industry $\times$ year fixed effects hold a bank's industry-specific lending capacity constant. Because each industry is classified as either military or civilian, these fixed effects also absorb any change in a bank's overall appetite for defense lending. Second, firms in the same country and sector (military or civilian) receive multiple loans in the same year, so host country $\times$ military sector $\times$ year fixed effects hold demand constant for military and civilian firms within each country-year.

Table 4 reports estimates of equation (8) with these fixed effects. Column (1) reproduces our baseline results, column (2) adds the bank $\times$ industry $\times$ year fixed effects, and column (3) instead adds the host country $\times$ military sector $\times$ year fixed effects. Columns (4)–(6) replicate columns (1)–(3) but also include bank $\times$ firm fixed effects to control for assortative matching between banks and firms and time-invariant relationship characteristics (Chodorow-Reich, 2014; Schwert, 2018).¹⁹

When we hold each bank's industry-specific credit supply fixed (columns (2) and (5)), cross-border lenders still reallocate credit toward military firms ($\beta_3 = 0.444$ and 1.247), while the civilian retrenchment weakens. When we instead hold fixed the credit demand of military and civilian firms in each country-year (columns (3) and (6)), the pattern reverses: β_3 shrinks and becomes insignificant, while β_1 remains negative and significant. In these columns, the military differential disappears: relative to domestic banks, cross-border lenders treat military and civilian firms alike, and the net military effect is negative but insignificant. These patterns are consistent with Predictions 1 and 2: a supply-driven flight home in civilian lending and

¹⁸A natural alternative would compare interest rate spreads on military versus civilian loans across conflict and non-conflict countries. However, spread data are too sparse for such an analysis: they are available for 38.3% of U.S. loans but for only 1.7% of non-U.S. loans.

¹⁹The number of observations varies across columns because more saturated fixed-effects structures drop singleton cells.

demand accommodation in military lending. Had cross-border lenders been targeting military firms on the supply side, the military differential would have persisted in columns (3) and (6). We now test more directly whether conflict raises the revenues and profitability of military firms (Section 6.2), and whether domestic banks lose the capacity to meet the resulting credit demand (Section 6.3).

6.2 Military firm performance during conflicts

Prediction 2 rests on the assumption that conflict raises the pledgeable income of military firms while lowering that of civilian firms (equation (5)). We now test an observable implication of this assumption: that military firms' revenues and profitability rise relative to those of civilian firms during conflicts. To do so, we apply local projections (Jordà, 2005) to Compustat data on 70,533 civilian and 13,439 military firms across 124 countries.

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

$$y_{fict+h} = \theta_f + \lambda_{ci} + \nu_{ct} + \omega_{it} + \beta_h \cdot Conflict_{ct} \times Military_i \quad (9)$$

$$+ \rho_1 \cdot y_{fict-1} + \rho_2 \cdot y_{fict-2} + \varepsilon_{fict+h},$$

where y_{fict+h} is the log of total revenues or the ratio of EBIT to total assets of firm f in four-digit SIC industry i in country c at horizon h ($h = 0, \dots, 8$) following conflict year t . Both measures are winsorized at the 2.5th and 97.5th percentiles. Because revenues are zero or missing for some firm-years, the revenue regressions have fewer observations than the profitability regressions.

We include firm fixed effects (θ_f) for time-invariant firm traits, country $\times$ industry fixed effects (λ_{ci}) for structural differences in industrial specialization, country $\times$ year fixed effects (ν_{ct}) for country-specific time-varying shocks, and industry $\times$ year fixed effects (ω_{it}) for global industry-level shocks. We estimate equation (9) by OLS with high-dimensional fixed effects and cluster standard errors by country $\times$ year. We expect $\beta_h > 0$: rising defense demand should allow military firms to outperform civilian firms during violent conflicts.

Figure 3 reports the estimates of equation (9). We find positive and highly significant coefficients β_h for military firms' revenues (Panel A) and operating profitability (Panel B), indicating that military firms grow faster and become more profitable than civilian firms during violent conflicts. Economically, military firms' revenues rise by 10.7% relative to

civilian firms in the conflict year ($h = 0$) and by 20.3% four years later. This sizable effect only gradually reverses over the following four years. In parallel, operating profitability (EBIT over total assets) rises by 1.1 percentage points relative to civilian firms in the conflict year and by about 1.5 percentage points one year later ($h = 1$), roughly a third of the median EBIT-to-assets ratio of 4.2%. The effect then fades gradually but remains significant through year six.²⁰ These dynamics increase both military firms' demand for credit and their attractiveness to lenders. We next ask why this additional demand is met disproportionately by cross-border rather than domestic lenders.

6.3 Domestic banking capacity and lender specialization

Violent conflicts coincide with a sharp weakening of domestic banking systems. In a country-level event study based on the World Bank Global Financial Development Database, we compare conflict countries with matched non-conflict countries, taking the last pre-conflict year as the reference period. Figure IA.6 shows that relative to their pre-conflict level, real deposits fall by about 10% in the conflict year, by 25% one year after onset, and by 34% and 35% two and three years after onset, with the declines statistically significant from the year after onset. Real bank loans follow a similar path, falling to about 11% below their pre-conflict level in the conflict year and 36% below it after three years. Meanwhile, the ratio of non-performing loans rises by 6 percentage points within three years.²¹ Conflict thus drains the funding base of domestic banks, curtails their lending, and weakens their balance sheets just as military firms' demand for credit rises.

Demand accommodation has three further implications. First, if cross-border lenders step in where domestic banks cannot, the military expansion should be larger where domestic banking systems are shallower (Prediction 3). Table IA.6 splits countries by their sample-average ratio of banking assets to GDP into the bottom tercile and the upper two terciles. The reallocation coefficient β_3 is about four times as large in shallow systems (column (2)),

²⁰Because the local projections use the baseline classification, β_h may partly reflect civilian demand in broad dual-use industries, such as telecommunications, that coincides with conflict. Section 5.2.3 shows that the lending reallocation holds under narrower classifications that exclude these industries.

²¹These declines are consistent with Benmelech and Monteiro (2025b), who find that real domestic credit falls by 22% across 115 conflicts since World War II and attribute this supply-driven contraction to the erosion of collateral values. They also document a substantial fall in deposits relative to GDP, which they link to a loss of confidence in banks.

partly reflecting a sharper civilian retrenchment in these systems. The net military effect ($\beta_1 + \beta_3$) is also larger in shallow systems, but the difference is not statistically significant. Second, if the expansion reflects higher pledgeable income rather than lending to distressed borrowers at wartime premia, maturities for military borrowers should not tighten. They do not: during conflicts, cross-border lenders lengthen loan maturities for military firms while becoming less likely to extend long-maturity loans to civilian firms (Section 5.2.2). Third, if cross-border lenders step in because they have capital that impaired domestic banks lack, rather than because they know the military sector better, the expansion should not be concentrated among lenders that specialized in military lending before the conflict. Indeed, β_3 barely varies with a lender’s pre-conflict share of military lending ($p = 0.61$; Table IA.13).

While demand accommodation explains what cross-border lenders respond to, it does not explain where these lenders come from or whether political alignment shapes the allocation of their credit. We turn to these questions in Section 7.

7 Geopolitical alignment and military lending

Governments lend to their allies in wartime, and we now ask whether private lenders do the same. Lenders from many countries could meet the wartime credit demand documented in Section 6, and whether they do may depend on their home country’s geopolitical relationship with the conflict country. We contrast three views.

Under *alliance finance*, the private analogue of the official war lending documented by Horn et al. (2026), lenders finance the defense sectors of geopolitically aligned countries. They may do so either by choice or at their home governments’ direction, extending into wartime the role that political alignment plays in peacetime capital allocation (Kempf et al., 2023). Military lending should then expand mainly within geopolitical blocs, and more so among state-owned lenders, which are more exposed to political influence (Bircan and Saka, 2021; Koetter and Popov, 2021).

In contrast, under *outsider finance*, lenders finance the defense sectors of politically distant countries. Social norms constrain the financing of controversial industries (Hong and Kacperczyk, 2009), and many banks and institutional investors formally exclude weapons producers from their portfolios. Financing a war also exposes a lender to scrutiny from regulators, depositors, the media, and other stakeholders at home. This scrutiny is plausibly most

intense when a conflict involves an ally and weakest when it is politically remote. Banks are known to shift activities that are constrained at home to markets where the constraints bind less and public attention is lower (Ongena, Popov and Udell, 2013; Laeven and Popov, 2023). Because these constraints apply to state-owned and private lenders alike, military lending should then expand mostly across geopolitical blocs, with no difference by ownership.

Lastly, under *arm’s-length finance*, lenders go wherever wartime credit demand is unmet, regardless of alignment, so military lending should expand both within and across blocs, with no difference between state-owned and private lenders. Outsider and arm’s-length finance can produce the same pattern across lender–borrower country pairs (dyads) if unmet wartime demand happens to be concentrated in conflict countries that are politically distant from most lenders. They differ, however, in what they predict for two cross-border lenders that face the same conflict destination: under outsider finance, the non-aligned lender lends more to military firms because it faces less scrutiny at home, whereas under arm’s-length finance the two lend alike.

Because conflict countries in different blocs also differ in how much wartime demand their domestic banks can meet, we compare lenders from different blocs that lend to the same conflict country in the same year, as the host country $\times$ year fixed effects in equation (8) ensure. We replace the *Foreign* indicator in that equation with indicators for the lender’s geopolitical bloc (Section 7.1), the lender–borrower bloc pair (Section 7.2), and state versus private ownership (Section 7.3). To separate outsider from arm’s-length finance, Section 7.2 also compares aligned and non-aligned lenders directly within the same host country, sector, and year.

7.1 Lender origin

We classify lender countries in two ways. The first uses formal alliances and forums: NATO (or, alternatively, the G7); BRICS (Brazil, Russia, India, China, and South Africa); and all other countries.²² The second classification uses the UN General Assembly ideal points of Bailey et al. (2017), updated through 2023. An ideal point summarizes a country’s foreign-policy position in a given year as a single number, estimated from its votes in the General Assembly. Because the estimates are anchored on resolutions that recur across sessions, ideal

²²Our NATO bloc includes 29 countries: all current members except Montenegro (owing to data limitations) and Finland and Sweden (which joined after our sample period).

points are comparable over time, and their single dimension largely reflects a country’s stance toward the U.S.-led international order. In each year, we compare each country’s ideal point with those of the United States and China. Countries in the quartile closest to the United States are classified as *West*, those in the quartile at the opposite end of the scale, anchored by China, as *East*, and those in the two middle quartiles as *Neutral*. Each lender country is assigned to the bloc it occupied in $t - 1$, so the classification is predetermined relative to the lending year. We use the contemporaneous bloc only when the lagged record is unavailable. Table IA.14 lists the resulting blocs and the assignment rules for territories and non-UN entities.

Cross-border lenders from every bloc respond to violent conflicts in a similar way (Table 5): they cut civilian lending by similar amounts (β_1 between -0.217 and -0.298) and reallocate toward military firms (β_3 between 0.424 and 0.644 , all significant at the 1% level). The net military effect is significant only for lenders from outside NATO, the G7, and BRICS ($p < 0.05$); for NATO, G7, and BRICS lenders it is positive but imprecise. Under the UN classification (column (3)), the net military effect is about 30% for West-origin lenders, 48% for Neutral-origin lenders, and 42% for East-origin lenders (significant at the 10%, 5%, and 5% levels, respectively).

7.2 Within-bloc versus cross-bloc lending

We now also assign borrower countries to UN blocs, which yields nine lender–borrower dyads. Conflict borrowers span all three blocs: 4 are West, 11 Neutral, and 9 East in at least one conflict year. Some, such as Russia, India, Sri Lanka, and Turkey, switch blocs over time (Table IA.15). Western lenders provide 83% of cross-border loans in the dyad sample, but all nine dyads contain loans (Table IA.16).

Table 6 reports the results. Military lending expands in several cross-bloc dyads but in no within-bloc dyad. In Eastern conflict countries, Western lenders raise military lending ($e^{\beta_1 + \beta_3} - 1$) by about 59% and Neutral lenders by a similar but imprecisely estimated 64%, whereas Eastern lenders do not. Eastern lenders raise military lending to Neutral conflict countries by 55%, and military lending rises by 35% between Neutral countries, which are aligned with neither bloc. In the dominant West-to-Neutral dyad, which carries 60% of conflict-year cross-border loans, lenders reallocate strongly toward military firms

($\beta_3 = 0.413$). Within the Western bloc, military lending contracts: Western lenders cut civilian lending to Western conflict countries by 36% and military lending by 70%.

A pooled test on the Western and Eastern dyads confirms that relative to domestic banks, non-aligned cross-border lenders increase military lending by about 64%, whereas the estimate for aligned lenders is negative and insignificant. The difference is significant at the 1% level (Table IA.17). This test, however, compares lenders that largely serve different conflict countries. The direct test instead compares aligned and non-aligned lenders within the same host country $\times$ sector $\times$ year cell, using cross-border loans only (Table IA.18). Once they face the same destination, aligned and non-aligned lenders respond alike: the difference in their net military response is small and insignificant when West–East lenders lend to the same country (0.028) or finance the same firm in the same year (-0.051), and precisely estimated at close to zero in the three-bloc comparison (-0.021 , SE 0.101).

These results reject alliance finance, which predicts within-bloc expansion. The dyadic pattern alone fits both outsider and arm’s-length finance, but the direct test separates them: conditional on the destination, non-aligned lenders do not lend more to military firms than aligned lenders, and the three-bloc estimate is precise enough to rule out a lender-side effect large enough to generate the dyadic gaps in Table 6. The evidence therefore points to arm’s-length finance: lenders accommodate unmet wartime demand where it arises, and that demand is concentrated outside the Western bloc, where most cross-border lenders are headquartered.

Our institutional classification confirms the absence of within-bloc expansion (Table IA.19). Military lending does not expand from NATO to NATO, where Turkey is the only conflict borrower, or from BRICS to BRICS. Because these memberships are fixed at their current composition, this classification is a robustness check on the time-varying UN-voting blocs rather than a measure of alignment in the lending year. Across blocs, cross-border lenders reallocate toward military firms from NATO and other countries to BRICS, and from BRICS and other countries to NATO.

Lastly, geographic distance does not drive any of these patterns. When we add the log distance between the capitals of the lender’s and the borrower’s countries to equation (8), interacted with *Conflict* and *Military*, military lending does not rise with distance among cross-border lenders, whether we control for the *Foreign* interactions in the full sample or restrict the sample to cross-border loans.

7.3 State-owned and private lenders

Under alliance finance, governments steer military credit toward their allies, so state-owned banks should expand military lending more than private banks. We instead find that private and state-owned cross-border banks cut civilian lending and reallocate toward military firms by similar amounts (β_3 of 0.544 and 0.535; net military effects of 38% and 36%; Table IA.20, column (2)). Banks and non-bank lenders (classified as in Aldasoro, Doerr and Zhou, 2025) also reallocate similarly, although only banks retrench from civilian firms (column (1)), so the net military effect is larger for non-banks.

The ownership result thus adds to the evidence against alliance finance. Together with the within-destination test in Section 7.2, it confirms that wartime military credit follows unmet demand, not political alignment.

8 Firm-level evidence

The previous sections show that cross-border lenders cut credit to civilian firms and meet wartime military credit demand that domestic banks cannot accommodate. Firms that borrowed more from cross-border lenders before the conflict should therefore be more affected: pre-conflict exposure should predict weaker balance sheets and real activity among civilian firms but stronger performance among military ones. We test this by relating firms' conflict-period outcomes to the cross-border share of their pre-conflict syndicated borrowing.

We start our analysis by merging Compustat with DealScan for firms in conflict countries. Because many Compustat firms have no DealScan record, we keep all firms with positive pre-conflict long-term debt and set their pre-conflict syndicated borrowing to zero if they do not appear in DealScan. We measure each firm's exposure as the share of cross-border loans in its total syndicated borrowing during $[t^* - 3, t^* - 2]$, where t^* is the first conflict year in the firm's country:

$$Foreign\ Share_{fsc} = \frac{\sum_b \sum_{\ell=2}^3 Foreign\ Loan_{bf,t^*-\ell}}{\sum_b \sum_{\ell=2}^3 Total\ Loan_{bf,t^*-\ell}}. \quad (10)$$

We exclude $t^* - 1$ to avoid anticipation effects (Figure 2, Panel A) and estimate the

following cross-sectional regression:

$$\begin{aligned} \ln(1 + \bar{Y}_{fsc}) = & \psi_{cst*} + \beta_1 \cdot Foreign Share_{fsc} \\ & + \beta_2 \cdot Foreign Share_{fsc} \times Military_s \\ & + \tau \cdot \mathbb{1}\{Borrowing\}_{fsc} + \rho \cdot \ln(1 + \bar{Y}_{fsc}^{pre}) + \varepsilon_{fsc}, \end{aligned} \quad (11)$$

where $\bar{Y}$ is average total liabilities, total assets, revenue, cash, or receivables over $[t^*, t^* + 2]$, and $\bar{Y}^{pre}$ is the corresponding outcome averaged over $[t^* - 3, t^* - 2]$. $\mathbb{1}\{Borrowing\}$ equals one for firms that borrowed from any syndicated lender during $[t^* - 3, t^* - 2]$. Firms without syndicated borrowing have $Foreign Share = 0$, and the indicator absorbs the average level difference between borrowers and non-borrowers. β_1 and β_2 are therefore identified from variation in foreign share among syndicated borrowers: β_1 is the foreign-share slope for civilian firms, β_2 the additional slope for military firms, and $\beta_1 + \beta_2$ the net slope for military firms. Because each regression controls for the outcome's pre-conflict level, the coefficients can be read as differences in growth from the pre-conflict to the conflict window.

Host country $\times$ sector $\times$ first-conflict-year fixed effects (ψ_{cst*}) absorb shocks common to firms in the same sector (military or civilian) in a given conflict country and onset year. We weight observations by average revenue over $[t^* - 3, t^* - 2]$, so economically larger firms receive greater weight, and cluster standard errors by host country $\times$ four-digit SIC industry.

Equation (11) yields conditional associations, not causal effects: firms that borrowed more from cross-border lenders before the conflict may differ from other firms in persistent ways. Three features of the design nevertheless help address this concern: exposure is measured before the conflict begins, each regression controls for the outcome's own pre-conflict level, and a placebo test below checks whether the same patterns already appear before conflicts.

Table 7 reports the estimates for up to 233 military and 2,661 civilian firms in 12 conflict countries. Panel A shows a sharp divergence between civilian and military firms. Among civilian firms, greater pre-conflict reliance on cross-border lenders is associated with lower conflict-period liabilities, assets, revenues, and cash. A 10 percentage-point increase in *Foreign Share* is associated with approximately 7.9% lower total liabilities, 3.6% lower total assets, 4.5% lower revenues, and 6.9% lower cash. The coefficient for receivables is also negative but statistically insignificant. The interaction with *Military* is positive and highly significant in all five columns, showing that these associations differ sharply for military

firms. The net military slopes imply that a 10 percentage point higher foreign exposure is associated with 15.1% more total assets, 12.9% higher revenues, and 14.3% more receivables. The net slopes for cash and total liabilities are positive but imprecisely estimated. Greater pre-conflict reliance on cross-border lenders is thus associated with stronger conflict-period performance among military firms but weaker performance among civilian firms.

Placebo. Cross-border lenders may select firms that were already on different trajectories before the conflict, in which case *Foreign Share* could proxy for pre-existing firm characteristics. Panel B of Table 7 therefore moves the outcome window to $[t^* - 5, t^* - 4]$ and controls for the same outcome over $[t^* - 7, t^* - 6]$. Both windows precede the $[t^* - 3, t^* - 2]$ period used to measure exposure to cross-border lenders. The foreign-share coefficient is statistically insignificant for all five outcomes, as are all five net military slopes, which for assets and revenue are essentially zero. The interaction with *Military* is nevertheless statistically significant for revenue and weakly significant for receivables, but at only about one-third of its conflict-period size. The large net associations in Panel A thus emerge during conflicts.

9 Conclusion

In this paper, we show that violent conflicts do not induce a uniform retreat of cross-border lenders but instead reallocate international credit across sectors. Relative to domestic banks, cross-border lenders cut lending to civilian firms by about half but more than double lending to military firms, at longer maturities. The civilian retrenchment is supply-driven, whereas the military expansion accommodates credit demand that impaired domestic banks cannot fully meet, and is larger where domestic banking systems are shallow. Firm-level outcomes are consistent with these lending patterns: among military-related firms, greater pre-conflict exposure to cross-border lenders is associated with better performance during conflict, whereas among civilian firms it is associated with weaker performance.

Taken together, the evidence is consistent with a dual-track structure of war finance. Sovereigns rely more heavily on official external finance, while military-related firms can draw on private cross-border credit when domestic intermediation is impaired. The two tracks also diverge politically: official war lending follows alliances (Horn et al., 2026), whereas private military credit flows across geopolitical blocs rather than within them (and this pattern holds

whether we define blocs by UN General Assembly voting or by formal alliances).

Our findings are difficult to reconcile with state-directed war finance, since state-owned and private lenders respond similarly. Nor do they point to a lender-side political mechanism: aligned and non-aligned lenders respond alike once we compare them within the same conflict country, sector, and year. Instead, the geopolitical pattern reflects where unmet wartime demand arises. This result qualifies a growing literature on geopolitical fragmentation, which shows that in peacetime cross-border capital tilts toward politically aligned countries (Kempf et al., 2023). We show that such fragmentation is not universal: wartime demand can attract private capital regardless of geopolitical alignment.

More broadly, our findings suggest that financial integration does not simply transmit local shocks but redirects capital toward borrowers that become relatively more profitable as a result. In our setting, the same mobility of bank capital that draws credit away from civilian firms allows cross-border lenders to finance military-related firms when domestic banks are weak. The consequences of financial integration therefore depend not only on the size of a shock but also on how it alters the relative returns to capital across sectors.

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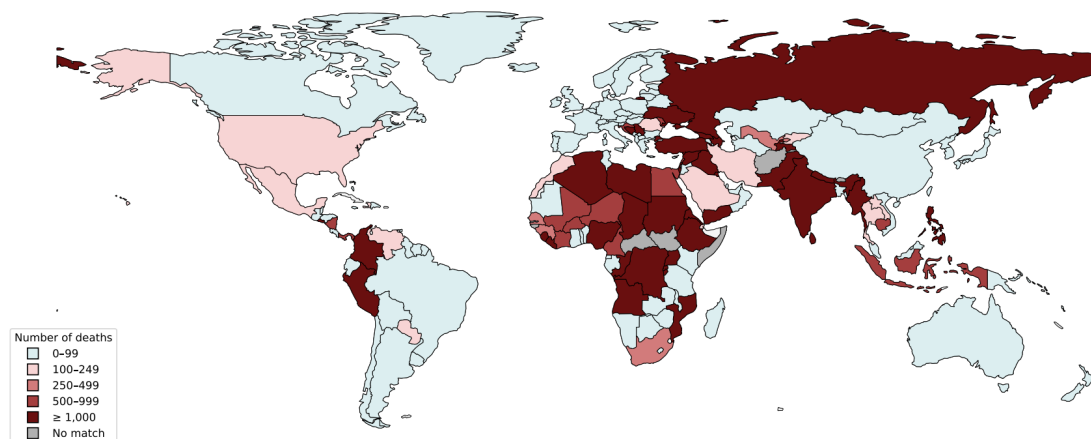
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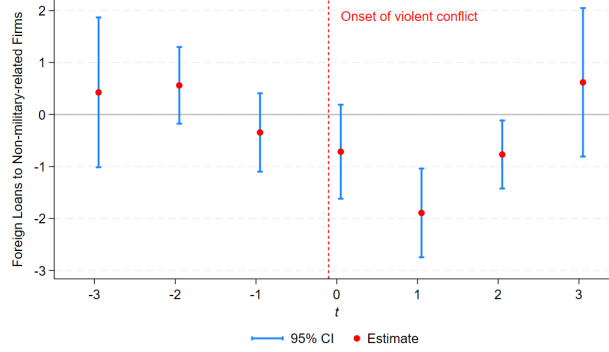
Figure 1. Conflict countries by annual battle-related deaths



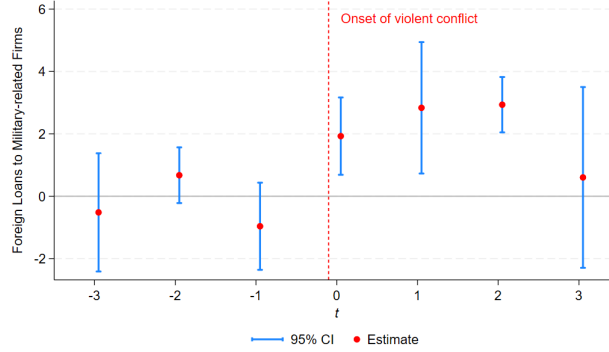
Note: This map shows countries by their highest recorded annual battle-related death count during 1989–2020, using the categories shown in the legend. “No match” indicates no overlap between the Uppsala Conflict Data Program and DealScan. Table IA.1 lists all conflicts. Data sources: Uppsala Conflict Data Program and DealScan.

Figure 2. Event-study analysis at the aggregate level

Panel A. β_1 : Foreign lending to civilian firms

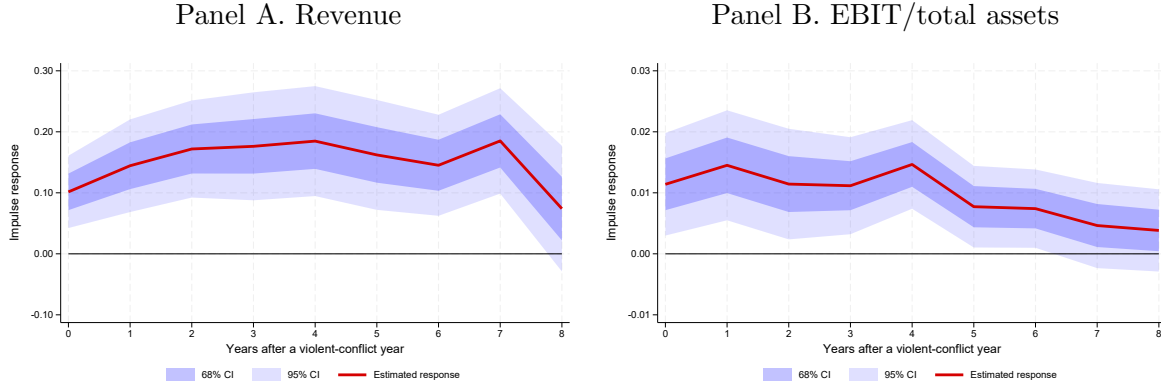


Panel B. β_3 : Foreign lending to military firms



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. All seven indicators from $t - 3$ to $t + 3$ are included, so each coefficient is measured relative to country-years outside this window and the figure decomposes those estimates by event year. Dots show point estimates and vertical bars show 95% confidence intervals. Data are from UCDP and DealScan.

Figure 3. Firm performance during violent conflicts: Local projections



Note: This figure reports estimates of β_h from equation (9) for horizons $h = 0, \dots, 8$ using firm-year data. The dependent variable is log total revenue in Panel A and the EBIT-to-total-assets ratio in Panel B. *Conflict* equals one in every year in which the firm's country experiences at least 1,000 battle-related deaths; consequently, the coefficients trace firm performance contemporaneously with and following a conflict year, rather than exclusively following conflict onset. *Military* equals one if the firm operates in a primary or dual-use military SIC industry (see Table IA.2). Each regression includes two lags of the dependent variable and firm, host country $\times$ year, SIC industry $\times$ host country, and SIC industry $\times$ year fixed effects. The number of observations declines from 787,929 at $h = 0$ to 353,057 at $h = 8$ in Panel A, and from 830,864 to 372,688 in Panel B. Shaded areas denote 68% and 95% confidence intervals. Data are from UCDP and Compustat. Standard errors are clustered at the host country $\times$ year level.

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*** (0.035)	0.647*** (0.033)		
Foreign $\times$ Conflict	β_1	0.333 (0.353)	0.166 (0.363)	-0.570* (0.325)	-0.627** (0.317)
Foreign $\times$ Military	β_2		-0.096* (0.050)		
Foreign $\times$ Conflict $\times$ Military	β_3		1.596*** (0.390)	1.596*** (0.390)	1.574*** (0.387)
Conflict		✓	✓	✓	✓
Host Region $\times$ Year FE		✓	✓	✓	✓
Conflict $\times$ Military FE			✓	✓	✓
Foreign $\times$ Military FE				✓	✓
Foreign $\times$ Host Country FE				✓	✓
Military $\times$ Year FE					✓
Foreign $\times$ Year FE					✓
N obs		22,624	22,624	20,334	20,334
N of Host Region $\times$ Year clusters		229	229	229	229
R^2 (adj.)		0.377	0.428	0.822	0.824

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 lender origin g to sector s in country c and year t , winsorized at the 99th percentile. *Foreign* equals one for cross-border lending and zero for domestic lending. *Conflict* equals one if the borrower's country experienced at least 1,000 battle-related deaths in a calendar year. *Military* equals one for loans to military-related SIC industries (Table IA.2). 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 $\times$ year. ***, **, * denote significance at 1%, 5%, and 10%.

Table 2. Cross-border lending to military firms during violent conflicts: Loan amounts and maturities

Dependent variable	Log loan amount			Loan maturity	
				Log	Upper quartile
	(1)	(2)	(3)	(4)	(5)
Foreign	-0.083*** (0.010)	-0.089*** (0.010)			
Foreign $\times$ Conflict	-0.226* (0.117)	-0.322*** (0.117)	-0.313*** (0.116)	-0.008 (0.024)	-0.044*** (0.010)
Foreign $\times$ Military		0.027*** (0.008)			
Foreign $\times$ Conflict $\times$ Military		0.509*** (0.105)	0.523*** (0.105)	0.118*** (0.030)	0.049*** (0.016)
Bank FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓	✓	✓
Conflict $\times$ Military FE			✓	✓	✓
Foreign $\times$ Military FE			✓	✓	✓
Military $\times$ Year FE			✓	✓	✓
Foreign $\times$ Year FE			✓	✓	✓
<i>N</i> obs	1,308,048	1,308,048	1,308,048	1,258,184	1,258,184
<i>N</i> of banks	14,021	14,021	14,021	13,681	13,681
R ² (adj.)	0.864	0.866	0.867	0.703	0.649

Note: This table reports estimates of equation (8). The dependent variable is the log loan amount in columns (1)–(3), log loan maturity in column (4), and a dummy equal to one if loan maturity is in the upper quartile of the maturity distribution in column (5); column (5) is a linear probability model. *Foreign* equals one for cross-border lending and zero for domestic lending; *Conflict* equals one if the borrower’s country experiences at least 1,000 battle-related deaths in a year; and *Military* equals one if the borrower operates in a primary or dual-use military SIC industry (see Table IA.2). The maturity sample is smaller because DealScan does not report maturity for all facilities. All regressions include the fixed effects indicated. Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Alternative definitions of military industries

	Dependent variable: $Loan_{bfsc}$				
	Primary & dual-use	Dual-use only	Primary only	LLM only	HS6 sanctions
	(1)	(2)	(3)	(4)	(5)
Foreign $\times$ Conflict	-0.313*** (0.116)	-0.317*** (0.117)	-0.268** (0.116)	-0.313** (0.125)	-0.317*** (0.119)
Foreign $\times$ Conflict $\times$ Military	0.523*** (0.105)	0.498*** (0.106)	0.379* (0.212)	0.450*** (0.097)	0.317*** (0.090)
Bank FE, Firm FE	✓	✓	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓	✓	✓
Foreign $\times$ 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 reports estimates of equation (8) under alternative definitions of *Military*. The dependent variable is the log loan amount. Column (1) reproduces the baseline, in which *Military* equals one for firms in the 10 primary military or 79 dual-use SIC industries listed in Table IA.2. Column (2) uses only the dual-use industries and column (3) only the primary military industries; each drops the other group from the sample rather than coding it as civilian (dropping 4,126 and 221,293 observations, respectively). Column (4) uses SIC codes identified by a large language model without reference to the export-control lists. Column (5) classifies a SIC industry as military if it contains at least one military or dual-use HS6 product subject to EU or UK sanctions (Chupilkin et al., 2026), mapped to SIC codes with the concordance of Pierce and Schott (2012); this classification involves no language model. *Foreign* equals one for cross-border lending and zero for domestic lending; *Conflict* equals one if the borrower's country experiences $\geq 1,000$ battle-related deaths in a year. Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Credit supply, credit demand, and bank-firm relationships

Dependent variable	$Loan_{bf_{sct}}$					
	Without bank $\times$ firm FE			With bank $\times$ firm FE		
	Baseline	Supply held fixed	Demand held fixed	Baseline	Supply held fixed	Demand held fixed
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign $\times$ Conflict (β_1)	-0.313*** (0.116)	-0.092 (0.193)	-0.275** (0.112)	-0.469* (0.251)	0.409 (0.336)	-0.397* (0.205)
Foreign $\times$ Conflict $\times$ Military (β_3)	0.523*** (0.105)	0.444** (0.204)	0.099 (0.133)	0.555** (0.235)	1.247** (0.633)	0.047 (0.364)
Bank FE, Firm FE	✓	✓	✓			
Bank $\times$ Firm FE				✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓	✓	✓	✓
Foreign $\times$ Year FE	✓	✓	✓	✓	✓	✓
Bank $\times$ Industry $\times$ Year FE		✓			✓	
Host Country $\times$ Military $\times$ Year FE			✓			✓
N obs	1,308,048	1,157,590	1,307,976	690,405	602,191	690,213
N of banks	14,021	8,048	14,021	6,721	2,095	6,719
R^2 (adj.)	0.867	0.877	0.868	0.894	0.907	0.896

Note: This table reports estimates of equation (8) with additional fixed effects to separate credit supply from demand. Columns (1) and (4) are baseline specifications. *Supply held fixed:* columns (2) and (5) add bank $\times$ industry $\times$ year fixed effects, so that each bank's industry-specific lending capacity is held constant within a year. *Industry* separates military/dual-use borrowers from the following DealScan industry groups: agriculture, mining, construction, manufacturing, transport, communications, energy, wholesale trade, retail trade, financial services, other services, and other. *Demand held fixed:* columns (3) and (6) add host country $\times$ military $\times$ year fixed effects, so that credit demand is held constant within each country-year for military and civilian borrowers separately. Columns (4)–(6) replace bank and firm fixed effects with bank $\times$ firm fixed effects, which absorb assortative matching and time-invariant relationship characteristics (Schwert, 2018; Chodorow-Reich, 2014). The number of observations and banks is lower in columns (2) and (4)–(6) because fixed-effect cells observed only once are dropped; no bank is excluded by design. The dependent variable is the log loan amount. *Foreign* equals one for cross-border lending and zero for domestic lending; *Conflict* equals one if the borrower's country experiences at least 1,000 battle-related deaths in a year; *Military* equals one if the borrower operates in a primary or dual-use military SIC industry (Table IA.2). Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Geopolitical origin and cross-border lending during violent conflicts

	Dependent variable: $Loan_{bfsc}$		
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 $\times B_1$ Foreign	-0.290** (0.115)	-0.298** (0.113)	-0.224** (0.100)
Conflict $\times B_2$ Foreign	-0.234** (0.112)	-0.232** (0.114)	-0.217** (0.103)
Conflict $\times B_3$ Foreign	-0.265** (0.111)	-0.243** (0.110)	-0.230** (0.116)
Conflict $\times$ Military $\times B_1$ Foreign	0.510*** (0.158)	0.501*** (0.158)	0.488*** (0.108)
Conflict $\times$ Military $\times B_2$ Foreign	0.424*** (0.109)	0.427*** (0.107)	0.565*** (0.145)
Conflict $\times$ Military $\times B_3$ Foreign	0.644*** (0.100)	0.616*** (0.107)	0.623*** (0.145)
Bank FE, Firm FE	✓	✓	✓
Home (Host) Country $\times$ Year FE	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓
Foreign (B_1 , B_2 , or B_3) $\times$ Military FE	✓	✓	✓
Foreign (B_1 , B_2 , or B_3) $\times$ 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 countries in bloc B_1	5	5	52
N countries in bloc B_2	29	7	67
N countries in bloc B_3	95	117	83

Note: The dependent variable is the natural logarithm of the loan amount. *Conflict* equals one if the firm's country experiences at least 1,000 battle-related deaths in a calendar year. *Military* equals one if the borrower operates in a primary military or dual-use SIC industry (see Table IA.2). Columns (1) and (2) classify foreign lenders by the geopolitical group of their home country: BRICS, NATO, and Other in column (1), and BRICS, G7, and Other in column (2). Column (3) classifies lender countries as West, East, or Neutral using UN General Assembly voting ideal points from Bailey et al. (2017), updated through 2023. Countries in the quartile closest to the United States are classified as West, those in the opposite quartile as East, and the two middle quartiles as Neutral. Each lender is assigned the bloc occupied by its home country in year $t - 1$. B_i *Foreign* equals one for a cross-border loan originated by a lender from bloc B_i ; domestic lenders form the omitted benchmark. The country counts in column (3) report distinct harmonized sovereign or metropole lender countries ever assigned to each bloc during 1989–2020. Because countries can change blocs over time, these counts are not mutually exclusive and therefore need not sum to the number of unique lender countries. All regressions include the fixed effects specified in the table. Data sources: UCDP, DealScan, and Bailey et al. (2017). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors clustered by bank are reported in parentheses.

Table 6. Lender and borrower blocs and cross-border lending during violent conflicts

	Dependent variable: $Loan_{bfsc}$		
	<i>West</i> to <i>West</i>	<i>Neutral</i> to <i>West</i>	<i>East</i> to <i>West</i>
Country bloc dyad B_{i1} :			
Country bloc dyad B_{i2} :	<i>West</i> to <i>Neutral</i>	<i>Neutral</i> to <i>Neutral</i>	<i>East</i> to <i>Neutral</i>
Country bloc dyad B_{i3} :	<i>West</i> to <i>East</i>	<i>Neutral</i> to <i>East</i>	<i>East</i> to <i>East</i>
	$i = 1$	$i = 2$	$i = 3$
Conflict $\times B_{i1}$ Foreign	-0.441* (0.226)	0.198 (0.300)	-0.241 (0.335)
Conflict $\times B_{i2}$ Foreign	-0.342*** (0.114)	-0.239** (0.121)	-0.283** (0.118)
Conflict $\times B_{i3}$ Foreign	-0.141 (0.129)	-0.237 (0.157)	-0.261* (0.139)
Conflict $\times$ Military $\times B_{i1}$ Foreign	-0.756*** (0.242)	-0.445 (0.408)	n/a
Conflict $\times$ Military $\times B_{i2}$ Foreign	0.413*** (0.109)	0.541*** (0.144)	0.719*** (0.170)
Conflict $\times$ Military $\times B_{i3}$ Foreign	0.607*** (0.197)	0.732*** (0.246)	0.072 (0.260)
Other foreign origin groups	Neutral, East	West, East	West, Neutral
Bank FE, Firm FE	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓
Foreign Dyad $\times$ Military FE	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓
Foreign Dyad $\times$ Year FE	✓	✓	✓
N home/(conflict) host countries in dyad bloc B_{i1}	26/4	10/4	7/3
N home/(conflict) host countries in dyad bloc B_{i2}	37/11	39/10	26/9
N home/(conflict) host countries in dyad bloc B_{i3}	23/8	29/8	23/7
N obs	1,299,029	1,299,028	1,299,028
N banks	13,966	13,966	13,966
R ² (adj.)	0.868	0.868	0.868

Note: The dependent variable is the log loan amount. *Conflict* equals one if the firm's country experiences at least 1,000 battle-related deaths in a year; *Military* equals one if the firm operates in a primary military or dual-use SIC industry (Table IA.2). Countries are assigned to West, Neutral, and East blocs by their UN General Assembly ideal points in $t - 1$ (Bailey et al., 2017); Table IA.14 gives the rules for territories and non-UN entities. B_{ij} *Foreign* are nine dummies equal to one if a cross-border lender from bloc i lends to a firm in bloc j ($i, j = 1, 2, 3$ for West, Neutral, and East); domestic loans are the omitted category. Columns correspond to the origin bloc i and rows to the destination bloc j . "n/a" indicates no identifying variation for that dyad-sector cell. Observation counts differ by one across columns because singleton observations are dropped. Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table 7. Exposure to cross-border lenders and firm outcomes

	Dependent variable (in logs)				
	Total balance-sheet liabilities (1)	Total assets (2)	Revenue (3)	Cash (4)	Receivables (5)
<i>Panel A: Conflict-period outcomes</i>					
Foreign share	-0.821** (0.400)	-0.365** (0.183)	-0.456** (0.205)	-0.717** (0.339)	-0.332 (0.256)
Foreign share $\times$ Military	1.131*** (0.297)	1.767*** (0.265)	1.667*** (0.215)	1.195*** (0.292)	1.670*** (0.228)
<i>Net foreign-share slope: Military</i>	0.310 (0.363)	1.402*** (0.330)	1.211*** (0.312)	0.478 (0.529)	1.337*** (0.308)
Host Country $\times$ Military $\times$ First-Conflict-Year FE	✓	✓	✓	✓	✓
<i>N</i> obs.	2,873	2,872	2,894	2,162	2,162
<i>N</i> clusters	811	811	813	709	709
<i>N</i> countries	12	12	12	11	11
R ² (adj.)	0.512	0.445	0.510	0.452	0.392
<i>Panel B: Earlier pre-conflict placebo outcomes</i>					
Foreign share	0.182 (0.457)	-0.159 (0.375)	-0.575 (0.446)	-0.274 (0.601)	0.349 (0.518)
Foreign share $\times$ Military	0.549 (0.412)	0.167 (0.331)	0.549** (0.259)	0.317 (0.303)	0.550* (0.315)
<i>Net foreign-share slope: Military</i>	0.730 (0.447)	0.008 (0.343)	-0.026 (0.460)	0.044 (0.740)	0.899 (0.575)
Host Country $\times$ Military $\times$ First-Conflict-Year FE	✓	✓	✓	✓	✓
<i>N</i> obs.	1,183	1,183	1,223	845	845
<i>N</i> clusters	469	469	475	402	402
<i>N</i> countries	10	10	10	9	9
R ² (adj.)	0.835	0.838	0.677	0.651	0.539

Note: This table reports conditional associations, without causal interpretation, between firm outcomes and the composition of syndicated borrowing before conflict onset. Panel A averages each outcome over the first three years from onset, $[t^*, t^* + 2]$, and controls for the same outcome over $[t^* - 3, t^* - 2]$. Panel B is a placebo that averages each outcome over $[t^* - 5, t^* - 4]$ and controls for it over $[t^* - 7, t^* - 6]$. *Foreign share* is the share of the firm's syndicated borrowing from cross-border lenders during $[t^* - 3, t^* - 2]$; firms without syndicated borrowing in that window have a zero foreign share, and all regressions control for $\mathbb{1}\{Borrowing\}$ (coefficient not reported). *Military* equals one if the firm operates in a primary military or dual-use SIC industry. Monetary outcomes are transformed as $\log(1 + x)$. Regressions are weighted by average firm revenue over $[t^* - 3, t^* - 2]$ and include host country $\times$ military status $\times$ first-conflict-year fixed effects. *Net foreign-share slope: Military* is the sum of the coefficients on *Foreign share* and *Foreign share $\times$ Military*. Data are from UCDP, DealScan, and Compustat. Standard errors clustered by host country $\times$ four-digit SIC industry are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Appendix A Variable definitions and sources

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

Variable	Definition	Source	Unit
$Loan_{gsct}$	The amount of syndicated loans aggregated to the lender origin (g)-sector (s)-country (c)-year (t) level, where g is 1 for cross-border lenders and 0 for domestic lenders and s is 1 for military and 0 for civilian sectors (defined below)	DealScan & Authors' calculations	0 or \$US
$Loan_{bfsc}$	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 country c 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	<i>Dummy</i> = 1 if country of the lender (or its parent) differs from the country of the firm	DealScan & Authors' calculations	0/1
Military	<i>Dummy</i> = 1 if the firm's SIC code pertains to either primary or dual-use SIC codes, as defined in Table IA.2	DealScan, Compustat, NAICS/SIC website & Authors' calculations	0/1
Battle-related deaths	Battle-related deaths per country and year	Uppsala Conflict Data Program (UCDP)	Persons
Conflict (j)	<i>Dummy</i> = 1 if battle-related deaths per country and year are greater than or equal to $j = 1,000$ (<i>baseline</i>), 750, 500, 250, 100.	UCDP & Authors' calculations	0/1
Post-conflict	<i>Dummy</i> = 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
Neighbor	<i>Dummy</i> = 1 if the firm's country borders a conflict country but is not itself in conflict in that year	UCDP & Authors' calculations	0/1
Foreign bank (nonbank)	<i>Dummy</i> = 1 if the loan is extended by a cross-border lender that is a bank (non-bank financial institution)	Aldasoro et al. (2025)	0/1
Foreign private (public) bank	<i>Dummy</i> = 1 if the loan is extended by a privately owned (state-owned) cross-border bank	Authors' calculations	0/1
Public debt	General government gross debt (% of GDP), averaged within country over the sample years with available data. A country is assigned to the low-fiscal-capacity group if <i>Public debt</i> is in the upper tercile of the cross-country distribution	IMF WEO & Authors' calculations	% of GDP
Bank assets	Total banking system assets (% of GDP), averaged within country over the sample years with available data. A country is assigned to the low-financial-capacity group if <i>Bank assets</i> is in the bottom tercile of the cross-country distribution	World Bank WDI & Authors' calculations	% of GDP

Table A.I – continued

Variable	Definition	Source	Unit
NATO (G7) (BRICS)	<i>Dummy</i> = 1 if a country belongs to NATO (G7) (BRICS)	Official NATO, G7, and BRICS membership lists	0/1
UN West (East)	<i>Dummy</i> = 1 (0) if the country's UN General Assembly ideal point lies in the quartile closest to the United States (in the quartile at the opposite, China-anchored end of the scale) in year $t - 1$; UN Neutral: the two middle quartiles in year $t - 1$	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
Debt	The log of the book value of all interest-bearing financial obligations of firm f in year t with maturity ≥ 1 year (<i>dltt</i>)	Compustat US+Global	Log \$US
Borrowing	<i>Dummy</i> = 1 if firm f had domestic or cross-border loans during $[t^* - 3, t^* - 2]$ in DealScan or 0 if firm f was observed only in Compustat and had positive <i>Debt</i> over the same horizon	DealScan & Compustat & Authors' calculations	0/1
Foreign Share	The sum of firm f cross-border loans over $[t^* - 3, t^* - 2]$ 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 <i>Debt</i> over the same horizon	DealScan & Compustat & Authors' calculations	0–1 share
EBIT	Earnings before interest and taxes, representing firm f 's ability to generate earnings from operations, independent of its capital structure or tax environment.	Compustat US+Global & Authors' calculations	% of total assets (<i>at</i>)
Revenue	The gross sales and other operating revenue of firm f in year t before deducting any costs, returns, or allowances (<i>revt</i>)	Compustat US+Global	Log \$US
Total balance-sheet liabilities	Total balance-sheet liabilities of firm f in year t (<i>lt</i>)	Compustat US+Global	Log \$US
Total assets	The book value of total assets of firm f in year t (<i>at</i>)	Compustat US+Global	Log \$US
Cash	Cash and short-term investments of firm f in year t (<i>che</i>)	Compustat US+Global	Log \$US
Receivables	Total receivables of firm f in year t (<i>rect</i>)	Compustat US+Global	Log \$US

Appendix B Descriptive statistics

Table B.I. Descriptive statistics

	N	Mean	SD	Min	25th	Median	75th	Max
Main variables								
$Loan_{gsct}$ (bn \$US)	22,832	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
Battle-related 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
Total balance-sheet liabilities ^b (log)	3,469	5.85	2.82	0	3.95	5.70	7.61	12.99
Total assets ^b (log)	3,469	6.61	2.17	3.06	4.89	6.37	8.20	10.49
Cash ^b (log)	2,813	3.11	2.09	0.12	1.35	2.82	4.67	6.87
Receivables ^b (log)	2,812	4.24	2.06	0.34	2.82	4.24	5.75	7.64
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	0.150	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
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
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 reports descriptive statistics for all variables used in the empirical analyses; Table A.I defines them. The sample period is 1989–2020. Because firms can report up to three SIC codes, some belong to both a primary military and a dual-use industry, so the means of *Military (primary)* and *Military (dual)* sum to more than the mean of *Military (primary & dual)*. The three UN-bloc indicators do not sum to one because 57,780 observations (4.4%), mainly loans by lenders headquartered in Taiwan, Hong Kong, and, before 2002, Switzerland, have no UN voting record in $t - 1$. Data are from UCDP, DealScan, Bailey et al. (2017), the NAICS/SIC website, and Compustat.

^a All firms in Compustat.

^b Firms in conflict countries observed before and after conflict onset, in Compustat only or in both Compustat and DealScan.

Internet Appendix

“Violent Conflict and Cross-Border Lending”

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Internet Appendix A Data and sample

This appendix provides additional information on the conflict episodes in our sample, the identification of military and dual-use industries, and the main source countries of syndicated lending to military-related firms in conflict zones.

A.1 Violent conflicts, 1989–2020

Table IA.1 lists all conflicts with at least 1,000 battle-related deaths in a given year during our sample period and describes those in the 16 countries that enter the loan-level analysis.

Table IA.1. Description of violent conflicts occurring in 1989–2020, by countries with $\geq$ 1,000 deaths

Country	Conflict Years	Conflict ID	Conflict Description
<i>Panel 1: Countries with > 0 syndicated loans during at least one conflict year</i>			
Algeria	1994–1999	386	The cancellation of the 1991 elections, which an Islamist party was expected to win, triggered a civil war between the government and Islamist armed groups, notably the Armed Islamic Group (GIA) and the Islamic Salvation Army (AIS), that sought to establish an Islamic state by force. Violence peaked in 1994–1999 with large-scale massacres, bombings, and severe repression, and largely subsided by the early 2000s as groups disarmed and the state reasserted control.
Angola	1989–1990, 1992–1994, 1998–1999, 2001	327; 387	Two overlapping conflicts: the civil war (1975–2002) between the ruling MPLA and UNITA, fueled by Cold War rivalries and regional interventions, and the separatist insurgency of the Front for the Liberation of the Enclave of Cabinda (FLEC) over control of the province’s oil. The civil war caused massive civilian casualties in the late 1980s and 1990s and ended after the death of UNITA leader Jonas Savimbi and a peace accord in 2002.
Colombia	1992, 1994, 1996, 1999–2005	289	A long-running conflict between the government, leftist guerrillas such as the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN), and right-wing paramilitaries, rooted in inequality, land distribution, and political exclusion. Violence and displacement, largely financed by drug trafficking, peaked from the early 1990s to the mid-2000s. A 2016 peace agreement with FARC formally ended the conflict, although violence persists in some regions.
Congo, DR	1996–2000, 2009, 2013–2014, 2017, 2020	265; 283; 314; 374; 429; 14692	Repeated large-scale conflicts involving domestic and foreign actors. The First (1996–1997) and Second (1998–2003) Congo Wars drew in numerous neighboring states and caused millions of deaths from violence, hunger, and disease. Rebel groups such as the AFDL, RCD, and later M23, as well as Rwandan and Ugandan forces, fought the government over power, territory, and resources. Instability persisted in the east, with operations by the Allied Democratic Forces (ADF), Kata Katanga, and Islamic State-linked groups.
Ethiopia	1989–1991, 1999–2000, 2020	267; 275; 329; 413; 11447	The Derg regime collapsed in 1991 after prolonged fighting with the Ethiopian People’s Revolutionary Democratic Front (EPRDF) and the Eritrean People’s Liberation Front (EPLF), paving the way for Eritrea’s independence in 1993. A border war with Eritrea in 1998–2000 caused heavy casualties before the Algiers peace agreement. In 2020, war broke out between the government and the Tigray People’s Liberation Front (TPLF), causing a severe humanitarian crisis until a ceasefire in 2022.

Continued on next page

Table IA.1 – continued

Country	Conflict Years	Conflict ID	Conflict Description
India	1989–1994, 1999–2010	218; 227; 251; 335; 347; 351; 364; 365; 421; 434; 11342; 11475	Multiple internal conflicts with separatist, ethnic, and ideological insurgents: tribal and ethnic rebel movements in the northeast (Assam, Nagaland, Tripura, and Manipur), Sikh separatists in Punjab, insurgent groups in Jammu and Kashmir, and left-wing movements (the MCC, PWG, and later CPI-Maoist) across central and eastern regions. India also fought several bouts of interstate hostilities with Pakistan over Kashmir.
Iraq	1991, 1997, 2003–2011, 2013–2018	259; 271; 338; 354; 371; 420	The 1991 Gulf War followed Iraq's invasion of Kuwait and caused extensive destruction. In the late 1990s, Iraqi forces clashed with Kurdish groups in the north. The 2003 U.S.-led invasion toppled Saddam Hussein and was followed by years of insurgency and sectarian violence. From 2013 onward, the Islamic State (IS) seized large parts of the country, triggering military operations by Iraqi forces, Kurdish Peshmerga, and an international coalition. By 2018, IS had lost most of its territory.
Israel	2014	234	The long-standing Israeli–Palestinian conflict over territorial claims to the same land dates back to the early 20th century and intensified after the establishment of Israel in 1948. In 2014, escalating tensions and rocket fire from Gaza led to the seven-week Gaza War (Operation Protective Edge) between Israel and Hamas, which involved extensive Israeli airstrikes and a ground invasion.
Liberia	2003	341	In the Second Civil War (1999–2003), the government of President Charles Taylor fought Liberians United for Reconciliation and Democracy (LURD) and the Movement for Democracy in Liberia (MODEL), amid ethnic and political grievances, regional interference, and competition over resources. Widespread atrocities prompted international intervention. The war ended with Taylor's resignation, the Accra Peace Agreement, and the deployment of UN peacekeepers.
Nigeria	2013–2020	297; 13641	Two Islamist insurgencies in the northeast. Jama'atu Ahlis Sunna Lidda'awati wal-Jihad (JAS, commonly known as Boko Haram) has fought to overthrow the government since 2009, using terrorism and mass abductions to pursue an Islamic state governed by Sharia law. The Islamic State West Africa Province (ISWAP), which split from Boko Haram, attacks military and civilian targets across the northeast and the Lake Chad Basin to establish territorial control.
Pakistan	2008–2015	218; 325; 404; 418	The government fought al-Qaida, Tehrik-i-Taliban Pakistan (TTP), and the Balochistan Republican Army (BRA). After the U.S. invasion of Afghanistan, al-Qaida operated within Pakistan, prompting Pakistani and U.S. military action against militant strongholds. The TTP (Pakistani Taliban) attacked military and civilian targets to impose strict Islamist rule, while the separatist BRA waged a nationalist insurgency in Balochistan over autonomy and resource control.
Philippines	1990–1991, 2000, 2003, 2017	209; 308; 14275	Long-standing conflicts with the Communist Party of the Philippines–New People's Army (CPP-NPA), which has waged a guerrilla insurgency since the late 1960s, and the Moro Islamic Liberation Front (MILF), which fought for the autonomy of the Muslim-majority south until a 2014 peace deal paved the way for the Bangsamoro Autonomous Region. Fighting against Islamic State–affiliated groups in the south culminated in the 2017 siege of Marawi City.
Russia	1995–1996, 1999–2000, 2002, 2004	401; 414	Two wars over Chechnya's bid for independence after the dissolution of the Soviet Union. In the First Chechen War (1994–1996), Chechen forces achieved a ceasefire and de facto independence. The Second Chechen War began in 1999 after a Chechen incursion into Dagestan and a series of bombings attributed to Chechen militants. By the early 2000s, Moscow had reasserted control under a pro-Russian government, although insurgency persisted.
Sri Lanka	1990–1993, 1995–2001, 2006–2009	313; 352	A civil war (1983–2009) between the government and the Liberation Tigers of Tamil Eelam (LTTE), which sought an independent Tamil state in the north and east. The conflict involved protracted fighting, suicide bombings, and large-scale offensives, with major escalations in the early 1990s and the 2000s. It ended in May 2009 with the military defeat of the LTTE after an intense final phase with heavy civilian casualties.

Continued on next page

Table IA.1 – continued

Country	Conflict Years	Conflict ID	Conflict Description
Turkey	1992–1999, 2016	338; 354; 383; 13902	Recurring armed conflict between the state and the PKK, whose insurgency escalated in the 1990s with intense clashes, security operations, and widespread displacement; far-left groups such as the DHKP-C also conducted sporadic attacks. In 2016, violence included renewed fighting with the PKK, major ISIS attacks in Istanbul and other cities, and a coup attempt by a military faction that caused significant casualties.
Ukraine	2014–2015	13219; 13243; 13246; 13247; 13306	The Maidan protests (2013–2014) ousted President Yanukovich and shifted Ukraine toward pro-European governance, which parts of the population in the east opposed. Russia annexed Crimea in 2014, and Russian-backed separatists declared the Donetsk (DPR) and Luhansk (LPR) People’s Republics, sparking armed conflict with the government. Russia provided significant military and logistical support to the separatists.

Panel 2: Countries with no syndicated loans during conflict years

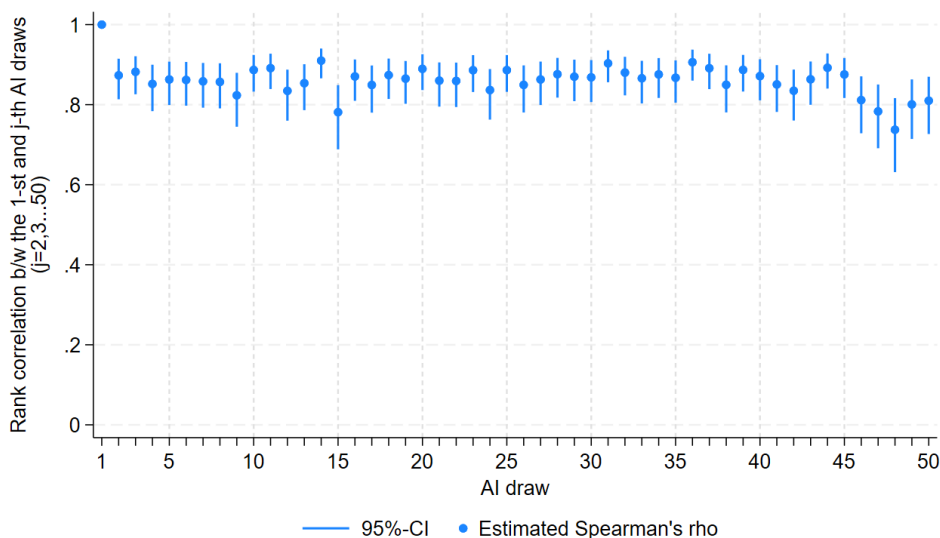
Azerbaijan (1992–1994, 2020; IDs 388, 396); Bosnia and Herzegovina (1992–1995; 389, 390, 397, 398); Burundi (2000–2002; 287); Chad (2006; 288); Congo (1997–1998; 408); El Salvador (1989; 316); Eritrea (1999–2000; 326, 409); Georgia (1993; 380, 392); Kuwait (1990; 371); Libya (2011, 2016, 2019; 11346, 13694); Mozambique (1989–1991; 332); Myanmar (1989, 1992; 221, 222, 231, 253); Nepal (2002–2005; 269); Peru (1989–1992; 292); Rwanda (1990, 1994, 1998, 2001; 374); Serbia (Yugoslavia) (1991, 1998–1999; 385, 412); Sierra Leone (1995, 1998–1999; 382); Sudan (1989–1992, 1995–2004, 2006, 2010–2012, 2015–2016; 288, 309, 314, 11344); Syria (2011–2020; 259, 299, 418, 426, 13042, 13604, 13809, 13886, 13902, 14609); Tajikistan (1992–1993, 1996; 395); Uganda (1989, 1996, 2004; 314); Yemen (1994, 2011–2012, 2014–2020; 230, 402, 13645).

Note: This table lists all conflicts with at least 1,000 battle-related deaths in a given year. Panel 1 describes the conflicts in the 16 countries with syndicated loans during at least one conflict year; these countries remain in our dataset after merging UCDP with DealScan and enter the loan-level analysis. Panel 2 lists 22 additional countries that did not borrow in the syndicated loan market during their conflict years, with conflict years and UCDP conflict IDs in parentheses; together with the Panel 1 countries, they enter the aggregate analysis in Section 5.1. Conflict IDs are from UCDP. Descriptions draw on UCDP.

A.2 Identifying military and dual-use industries

This subsection provides details on our classification of military-related industries (Section 3.2). We score the candidate industries with GPT-4o, accessed through the ChatGPT interface with default settings, in December 2024 and January 2025. The candidate list contains 124 four-digit SIC codes: 10 primary military industries and 114 potential dual-use industries. We submit the list 50 times, each time in a random order. The prompt refers the model to Annex I (List of Dual-Use Items) of the UK Strategic Export Control List and asks it to assess, for each SIC code, the likelihood (0–100%) that the industry produces dual-use items or has potential applications in the military sector. We average the 50 likelihoods for each code and classify a dual-use industry as military-related if its average exceeds 50%, which yields 79 dual-use industries. The 10 primary military industries are mixed in with the dual-use candidates without being flagged, and receive average likelihoods of 95–100%. Figure IA.1 shows that rank orders are highly consistent across the 50 runs, and Table IA.2 lists the resulting primary military and dual-use SIC codes.

Figure IA.1. Rank correlations across AI-based classification runs



Note: This figure plots Spearman rank correlations between the likelihoods from the first scoring run and those from each of the 49 subsequent runs. Section 3.2 describes how the 124 candidate SIC codes are drawn from the UK Military and Dual-Use Lists.

Table IA.2. Primary military and dual-use industries (four-digit SIC code)

SIC	Description	Share	Prob
Panel A: Primary military-related industries			
9711	National Security	0.054	99.7
3484	Small Arms	0.077	99.3
3489	Ordnance and Accessories, Not Elsewhere Classified	0.205	99.2
3482	Small Arms Ammunition	0.085	99.0
2892	Explosives	0.127	98.9
3764	Guided Missile and Space Vehicle Propulsion Units and Propulsion Unit Parts	0.307	98.9
3769	Guided Missile Space Vehicles Parts and Auxiliary Equipment, Not Elsewhere Classified	0.227	98.9
3483	Ammunition, Except for Small Arms	0.281	98.8
3761	Guided Missiles and Space Vehicles	0.656	98.7
3795	Tanks and Tank Components	0.171	97.6
Panel B: Dual-use industries			
Category 0 - Nuclear materials, facilities, and equipment			
3823	Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products	1.528	77.5
3829	Measuring and Controlling Devices, Not Elsewhere Classified	1.161	73.9
2819	Industrial Inorganic Chemicals, Not Elsewhere Classified	3.464	70.2
2869	Industrial Organic Chemicals, Not Elsewhere Classified	3.328	69.0
3559	Special Industry Machinery, Not Elsewhere Classified	2.487	67.1
3844	X-Ray Apparatus and Tubes and Related Irradiation Apparatus	0.236	65.9
3491	Industrial Valves	0.575	63.3
3462	Iron and Steel Forgings	0.796	59.4
3845	Electromedical and Electrotherapeutic Apparatus	1.448	58.1
3443	Fabricated Plate Work (Boiler Shops)	0.957	55.5
Category 1 - Special materials and related equipment			
3312	Steel Works, Blast Furnaces (Including Coke Ovens), and Rolling Mills	4.079	70.5
2836	Biological Products, Except Diagnostic Substances	0.954	66.4
3499	Fabricated Metal Products, Not Elsewhere Classified	0.936	55.8
Category 2 - Materials processing			
3823	Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products	1.528	77.5
3829	Measuring and Controlling Devices, Not Elsewhere Classified	1.161	73.9
3541	Machine Tools, Metal Cutting Types	0.778	72.7
3542	Machine Tools, Metal Forming Types	0.270	71.2
2899	Chemicals and Chemical Preparations, Not Elsewhere Classified	5.606	68.1
3549	Metalworking Machinery, Not Elsewhere Classified	0.209	64.3
3544	Special Dies and Tools, Die Sets, Jigs and Fixtures, and Industrial Molds	0.463	63.4
3567	Industrial Process Furnaces and Ovens	0.062	59.8
3821	Laboratory Apparatus and Furniture	0.506	59.8
Category 3 - Electronics			
3674	Semiconductors and Related Devices	5.314	82.6

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Table IA.2 – continued

SIC	Description	Share	Prob
3669	Communications Equipment, Not Elsewhere Classified	1.146	78.5
3825	Instruments for Measuring and Testing of Electricity and Electrical Signals	0.898	78.4
3679	Electronic Components, Not Elsewhere Classified	5.527	76.5
3571	Electronic Computers	1.839	74.1
5065	Electronic Parts and Equipment, Not Elsewhere Classified	2.198	73.1
3612	Power, Distribution, and Specialty Transformers	0.877	71.8
3675	Electronic Capacitors	0.359	71.8
3678	Electronic Connectors	0.444	71.6
3677	Electronic Coils, Transformers, and Other Inductors	0.341	70.5
3699	Electrical Machinery, Equipment, and Supplies, Not Elsewhere	2.676	69.8
3676	Electronic Resistors	0.118	67.5
3629	Electrical Industrial Apparatus, Not Elsewhere Classified	0.370	67.3
5063	Electrical Apparatus and Equipment Wiring Supplies, and Construction Materials	1.612	61.3
3824	Totalizing Fluid Meters and Counting Devices	0.213	59.1
3861	Photographic Equipment and Supplies	0.687	54.2
3469	Metal Stampings, Not Elsewhere Classified	0.381	50.5
Category 4 - Computers			
3572	Computer Storage Devices	1.105	71.2
7373	Computer Integrated Systems Design	2.953	66.6
3577	Computer Peripheral Equipment, Not Elsewhere Classified	2.526	62.4
3695	Magnetic And Optical Recording Media	0.341	61.1
3575	Computer Terminals	0.342	60.3
7371	Computer Programming Services	2.266	55.2
7372	Prepackaged Software	4.925	53.1
7374	Computer Processing and Data Preparation and Processing Services	2.514	52.8
7379	Computer Related Services, Not Elsewhere Classified	2.156	50.8
7376	Computer Facilities Management Services	0.271	50.4
Category 5 - Telecommunications and “information security”			
3669	Communications Equipment, Not Elsewhere Classified	1.146	78.5
3663	Radio and Television Broadcasting and Communications Equipment	2.067	76.0
3661	Telephone and Telegraph Apparatus	2.138	71.2
4812	Radiotelephone Communications	7.145	70.7
4813	Telephone Communications, Except Radiotelephone	9.144	64.6
4899	Communications Services, Not Elsewhere Classified	8.920	61.4
4822	Telegraph and Other Message Communications	1.008	60.3
3357	Drawing and Insulating of Nonferrous Wire	1.047	53.1
Category 6 - Sensors and lasers			
3826	Laboratory Analytical Instruments	0.782	71.7
3699	Electrical Machinery, Equipment, and Supplies, Not Elsewhere	2.676	69.8
3822	Automatic Controls for Regulating Residential and Commercial Environments and Appliances	0.361	50.4
Category 7 - Navigation and avionics			
3721	Aircraft	2.299	98.0
3724	Aircraft Engines and Engine Parts	1.512	96.8

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Table IA.2 – continued

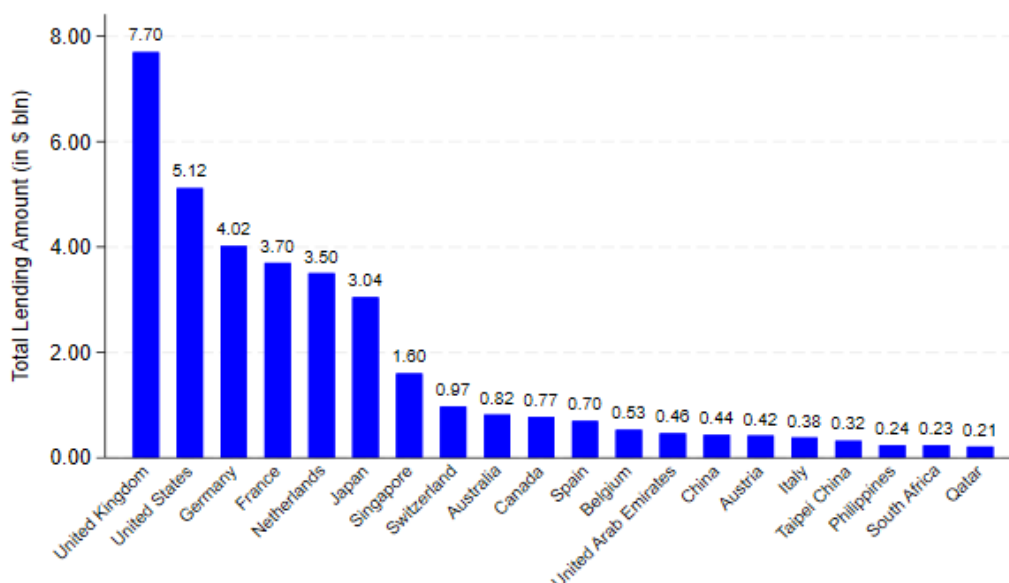
SIC	Description	Share	Prob
3812	Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems and Instruments	1.810	96.6
3728	Aircraft Parts and Auxiliary Equipment, Not Elsewhere Classified	1.982	94.2
3511	Steam, Gas, and Hydraulic Turbines, and Turbine Generator Set Units	0.902	78.0
3829	Measuring and Controlling Devices, Not Elsewhere Classified	1.161	73.9
3621	Motors and Generators	0.537	66.6
3519	Internal Combustion Engines, Not Elsewhere Classified	1.002	65.3
5088	Transportation Equipment and Supplies, Except Motor Vehicles	0.742	65.1
3566	Speed Changers, Industrial High-Speed Drives, and Gears	0.159	64.7
3594	Fluid Power Pumps and Motors	2.526	64.0
3492	Fluid Power Valves and Hose Fittings	0.199	63.2
3694	Electrical Equipment for Internal Combustion Engines	0.397	60.7
4581	Airports, Flying Fields, and Airport Terminal Services	2.419	59.8
3824	Totalizing Fluid Meters and Counting Devices	0.213	59.1
3463	Nonferrous Forgings	0.046	57.7
3536	Overhead Traveling Cranes, Hoists, and Monorail Systems	0.256	55.4
3357	Drawing and Insulating of Nonferrous Wire	1.047	53.1
3369	Nonferrous Foundries, Except Aluminum and Copper	0.110	50.4
Category 8 - Marine			
3731	Ship Building and Repairing	1.515	90.0
3823	Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products	1.528	77.5
3732	Boat Building and Repairing	0.400	69.9
3625	Relays and Industrial Controls	0.668	68.5
3519	Internal Combustion Engines, Not Elsewhere Classified	1.002	65.3
5088	Transportation Equipment and Supplies, Except Motor Vehicles	0.742	65.1
3561	Pumps and Pumping Equipment	0.728	59.8
8711	Engineering Services	5.125	55.2
Category 9 - Aerospace and propulsion			
9661	Space Research and Technology	0.040	97.2
3829	Measuring and Controlling Devices, Not Elsewhere Classified	1.161	73.9
5088	Transportation Equipment and Supplies, Except Motor Vehicles	0.742	65.1
3643	Current-Carrying Wiring Devices	1.192	55.6

Note: We search the UK Military List and the UK Dual-Use List of the UK Strategic Export Control List for military-related and dual-use terms and hand-collect the matching four-digit SIC codes on the NAICS website. Panel A shows the 10 primary military SIC codes; Panel B lists the 79 unique dual-use codes with an average likelihood of military application above 50% (Section A.2); a code can appear under several categories. *Share* is each code's share of bank-firm-year observations across all primary and dual-use industries; it sums to more than 100% because firms report up to three SIC codes and codes can appear under several categories. *Prob* is the average GPT-4o likelihood across the 50 runs. Industries are sorted by *Prob* within each category.

A.3 Main source countries of military lending

Figure IA.2 ranks the 20 home countries whose lenders provided the most syndicated credit to military-related firms in conflict countries during conflict years.

Figure IA.2. Top-20 countries in terms of military-sector lending 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 at least 1,000 battle-related deaths in a calendar year. Data sources: Uppsala Conflict Data Program and DealScan.

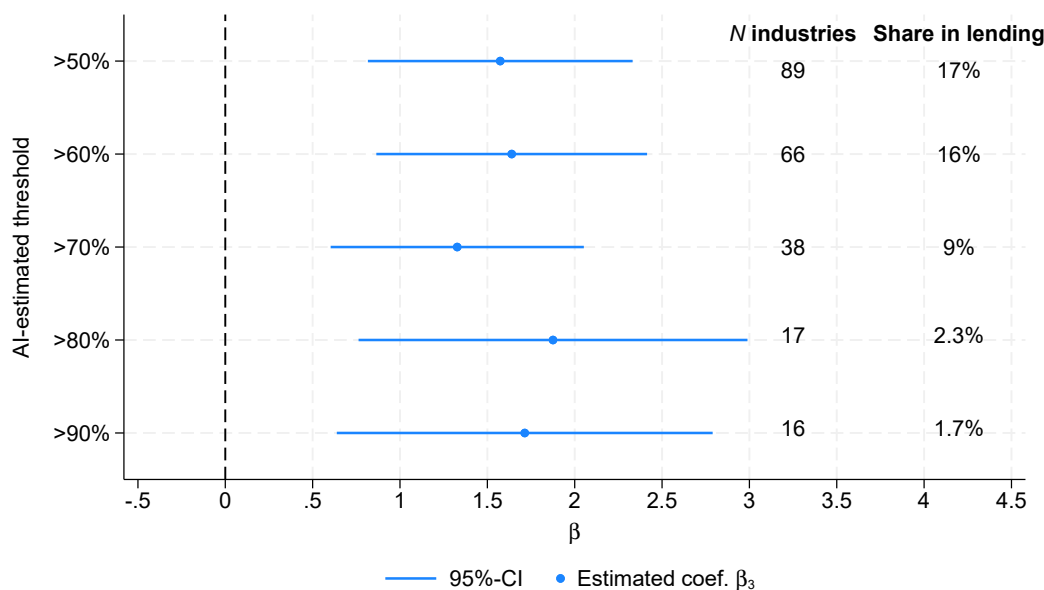
Internet Appendix B Aggregate results: further tests

This appendix supports Section 5.1 of the main text. Section B.1 describes the robustness tests for the aggregate-level results, and Section B.2 reports two sources of cross-country heterogeneity: sudden versus simmering conflicts and domestic fiscal and financial capacity.

B.1 Robustness

We examine the robustness of our aggregate-level findings to varying the classification of dual-use industries. We increase the AI-estimated likelihood threshold for military use from 50% to 90% in increments of 10 percentage points and check how the estimate of β_3 responds.

Figure IA.3. Estimates at the aggregate level using different subsets of dual-use industries

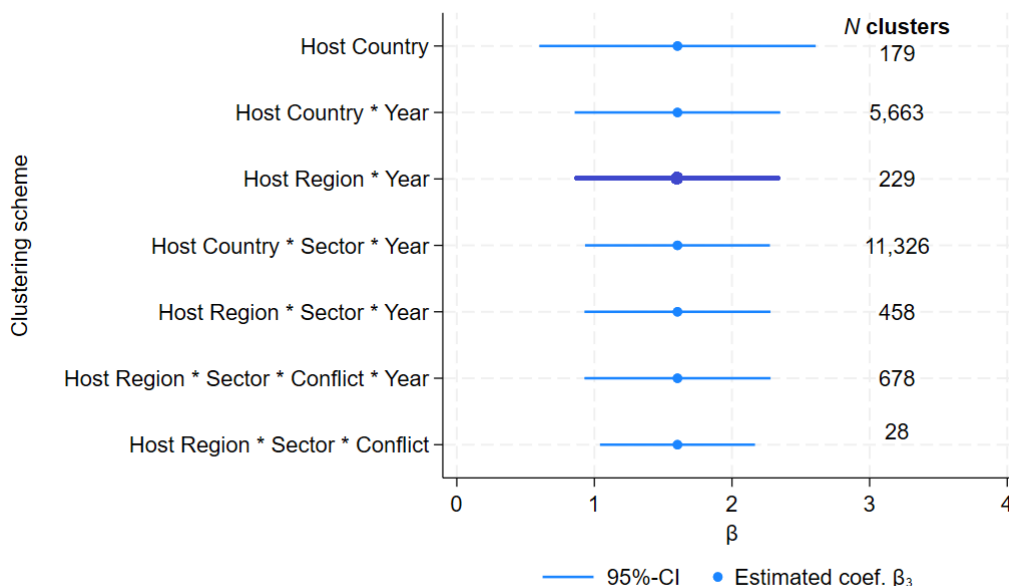


Note: This figure reports estimates of β_3 from the triple interaction $\text{Conflict} \times \text{Foreign} \times \text{Military}$ in equation (7), with 95% confidence intervals based on standard errors clustered by host region $\times$ year. We vary the AI-assigned likelihood threshold for classifying dual-use industries from 50% to 90% in 10 pp increments. Each point represents a different threshold, with the baseline 50% threshold marked in dark blue. *N industries* 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 $\geq 1,000$ battle-related deaths per year. Data: Uppsala Conflict Data Program and DealScan.

Figure IA.3 illustrates that the point estimate of β_3 remains robust across thresholds even as the number of military industries declines and their share in syndicated lending shrinks.

Second, we check the robustness of our inference to different clustering approaches. Figure IA.4 compares the baseline approach (clustering at the level of host region $\times$ year) to six alternatives: (i) host-country clusters; (ii) host country $\times$ year clusters; (iii) host country $\times$ sector $\times$ year clusters; (iv) host region $\times$ sector $\times$ year clusters; (v) host region $\times$ sector $\times$ conflict $\times$ year clusters; and (vi) host region $\times$ sector $\times$ conflict clusters. As Figure IA.4 indicates, our β_3 estimate remains statistically significant at the 5% level (and, in fact, at the 1% level) in each case.

Figure IA.4. 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 $\geq 1,000$ battle-related 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 dollar amount of lending), defined as $\ln(y + \sqrt{y^2 + 1})$, and estimate a linear version of equation (7) by OLS with high-dimensional fixed effects. Like the natural logarithm, this transformation compresses the right tail of the loan distribution, but unlike the logarithm it is well-defined at zero. Table IA.3 reports the results with host region $\times$ year fixed effects on the full panel and on the sample that PPML retains (columns (2) and (3)), and with host country $\times$ year fixed effects on the sample that PPML retains under those fixed effects (column (4)). The civilian retrenchment and the military reallocation are significant in every column, and the net military effect is positive throughout (significant at the 10% level or better).

Fourth, we replace the host region $\times$ year fixed effects with host country $\times$ year fixed effects (Table IA.4). These absorb *Conflict* and all other shocks at the country-year level. Because of the separation problem (Correia et al., 2020), the PPML estimator drops 45% of the observations, mainly country-years without any syndicated lending. The coefficient β_3 is virtually unchanged (1.551 in column (4), compared with 1.574 in Table 1). The coefficient β_1 follows the same pattern across columns as in the baseline: it is positive but insignificant without *Foreign $\times$ Host Country* fixed effects (columns (1)–(2)) and negative once they are added (columns (3)–(4)). In column (4), however, it is smaller than in the baseline and no longer significant. Its standard error is also smaller than in the baseline, so the loss of significance reflects a smaller point estimate, not a loss of precision. The net military effect, $\beta_1 + \beta_3$, is therefore larger than in the baseline (1.331 compared with 0.947) in column (4). Table IA.3, column (4), shows that the attenuation is specific to PPML: the IHS-OLS specification with host country $\times$ year fixed effects, estimated on the cells PPML retains, leaves the civilian retrenchment negative and significant.

Fifth, Figure IA.5 further shows that the aggregate military-lending result is not driven by any single conflict country. Re-estimating Table 1, column (4), while excluding each of the 16 active conflict borrowers one at a time yields positive estimates of β_3 in every case. The estimates range from 0.939 when Ukraine is excluded to 2.898 when India is excluded; in all cases, the leave-one-country-out confidence intervals remain positive and overlap with the baseline confidence interval. Thus, the aggregate reallocation toward military-related sectors does not hinge on any individual conflict-country episode.

Table IA.3. Aggregate-level analysis: Alternative transformation of the dependent variable

		$Loan_{gsct}$	$IHS(Loan_{gsct})$		
		Baseline PPML (1)	Full panel (2)	PPML sample (3)	PPML sample (4)
Foreign $\times$ Conflict	β_1	-0.627** (0.317)	-1.543*** (0.384)	-1.567*** (0.433)	-1.743** (0.786)
Foreign $\times$ Conflict $\times$ Military	β_3	1.574*** (0.387)	2.232*** (0.528)	2.471*** (0.596)	3.808*** (1.254)
<i>Net foreign military effect: $\beta_1 + \beta_3$</i>		0.947*** (0.228)	0.690* (0.396)	0.904** (0.451)	2.065* (1.062)
Conflict FE		✓	✓	✓	✓
Host Region $\times$ Year FE		✓	✓	✓	
Host Country $\times$ Year FE					✓
Conflict $\times$ Military FE		✓	✓	✓	✓
Foreign $\times$ Host Country FE		✓	✓	✓	✓
Foreign $\times$ Military FE		✓	✓	✓	✓
Military $\times$ Year FE		✓	✓	✓	✓
Foreign $\times$ Year FE		✓	✓	✓	✓
N obs.		20,334	22,832	20,334	12,164
N host region $\times$ year clusters		229	256	229	229
Pseudo R^2		0.825			
R^2 (adj.)			0.663	0.651	0.609

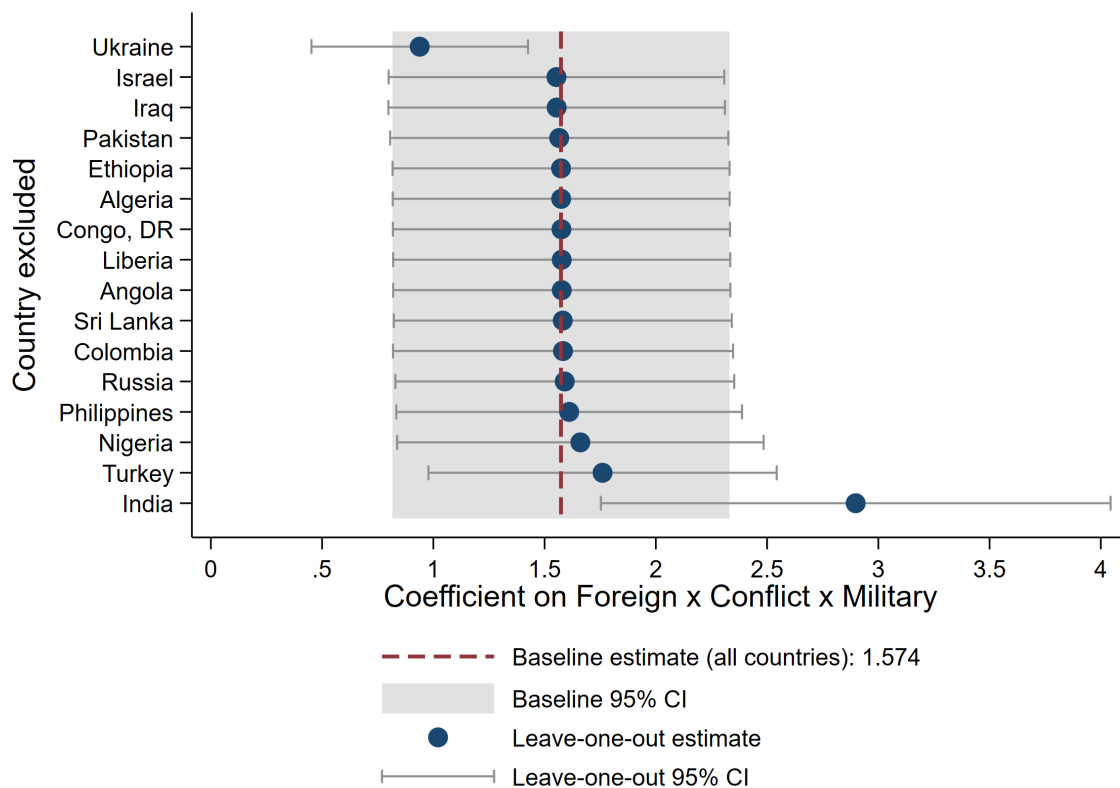
Note: Column (1) reproduces the preferred aggregate specification using Poisson Pseudo-Maximum Likelihood with high-dimensional fixed effects (Correia et al., 2020); its dependent variable is total lending measured in billions of US dollars. Columns (2)–(4) estimate the specification by OLS after transforming the underlying dollar amount of lending using the inverse hyperbolic sine, $IHS(y) = \ln(y + \sqrt{y^2 + 1})$. Loan amounts are winsorized at the 99th percentile before applying the transformation. Column (2) uses the full eligible balanced panel, and column (3) holds the sample fixed at the observations retained by PPML in column (1). Column (4) replaces host region $\times$ year with host country $\times$ year fixed effects and holds the sample fixed at the observations retained by a PPML estimation with the same fixed effects (Table IA.4, column (4)). On the full balanced panel, host country $\times$ year fixed effects leave the estimates in column (2) unchanged, because the *Foreign* $\times$ *Conflict* interactions vary only within host country-years. Because PPML and IHS-OLS use different functional forms, their coefficient magnitudes are not directly comparable. *Foreign_{gc}* equals one for cross-border lending and zero for domestic lending. *Conflict* equals one if the borrowing country experiences at least 1,000 battle-related deaths in a calendar year. *Military* equals one for primary or dual-use military industries (Table IA.2). *Net foreign military effect* reports the linear combination $\beta_1 + \beta_3$. Data are from UCDP and DealScan. Standard errors clustered by host region $\times$ year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IA.4. Aggregate-level analysis: More granular fixed effects

		Dependent variable: $Loan_{gsct}$			
		(1)	(2)	(3)	(4)
Foreign	β_0	0.623*** (0.035)	0.647*** (0.033)		
Foreign $\times$ Conflict	β_1	0.333 (0.353)	0.166 (0.363)	-0.177 (0.239)	-0.220 (0.235)
Foreign $\times$ Military	β_2		-0.096* (0.050)		
Foreign $\times$ Conflict $\times$ Military	β_3		1.596*** (0.390)	1.596*** (0.390)	1.551*** (0.383)
Host Country $\times$ Year FE		✓	✓	✓	✓
Conflict $\times$ Military FE			✓	✓	✓
Foreign $\times$ Military FE				✓	✓
Foreign $\times$ Host Country FE				✓	✓
Military $\times$ Year FE					✓
Foreign $\times$ Year FE					✓
N obs		12,440	12,440	12,178	12,164
N of host region $\times$ year clusters		229	229	229	229
Pseudo R^2		0.732	0.798	0.828	0.832

Note: This table estimates equation (7) after replacing host region $\times$ year fixed effects with host country $\times$ year fixed effects. Estimation uses Poisson Pseudo-Maximum Likelihood with high-dimensional fixed effects (Correia et al., 2020). The dependent variable is total lending $Loan_{gsct}$ by lender origin g to sector s in country c and year t , in billions of US dollars, winsorized at the 99th percentile. $Foreign_{gc}$ equals one for cross-border lending and zero for domestic lending. $Conflict$ equals one if the borrowing country experiences at least 1,000 battle-related deaths in a calendar year. $Military$ equals one for primary or dual-use military industries (Table IA.2). All regressions include the fixed effects shown. Data are from UCDP and DealScan. Standard errors clustered by host region $\times$ year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure IA.5. Leave-one-country-out estimates of aggregate military-lending reallocation



Note: This figure reports estimates of β_3 from Table 1, column (4), re-estimated after excluding one active conflict borrower country at a time. The dashed vertical line marks the baseline estimate using all countries, and the grey shaded band reports its 95% confidence interval. Horizontal bars report 95% confidence intervals from each leave-one-country-out regression. Standard errors are clustered by host region $\times$ year.

B.2 Cross-country heterogeneity

We study two sources of cross-sectional variation in our baseline aggregate results: sudden versus simmering conflicts and domestic fiscal capacity and banking system depth. Table IA.5 examines whether banks respond differently to sudden and simmering conflicts. We classify a conflict episode as *sudden* if battle-related deaths were below 250 in the year preceding the onset of conflict, defined by the 1,000-death threshold, and as *simmering* if deaths were already at least 250. The sample contains 29 sudden episodes spanning 66 conflict country-years and 43 simmering episodes spanning 130 conflict country-years. Nine additional episodes, spanning 25 conflict country-years, cannot be classified because the required pre-onset observation is unavailable. We estimate a single pooled PPML regression containing separate sudden, simmering, and unclassified conflict indicators, together with their interactions with *Foreign* and *Military*. Thus, conflict years belonging to the other categories are not included in the comparison group. Both the civilian retrenchment and the military reallocation are much stronger after sudden onsets than after simmering onsets, and equality is rejected for both coefficients ($p < 0.001$). After simmering onsets, the military reallocation remains positive and significant, whereas the civilian retrenchment is no longer significant.

Table IA.6 examines whether cross-border reallocation during conflict depends on host-country fiscal capacity and banking sector depth. Two distinct patterns emerge. First, the reallocation toward military firms is particularly pronounced in countries with less developed domestic banking systems, consistent with cross-border lenders substituting for limited local intermediation capacity. Second, the military reallocation is present regardless of fiscal strength but is larger in low-debt countries, where the civilian retrenchment is also stronger. If private cross-border credit substituted for constrained public war finance, the military reallocation should instead be largest where fiscal space is most limited. Cross-border lenders thus respond less in both directions in high-debt countries, consistent with sovereign risk limiting their pre-conflict exposure there.

Table IA.5. Aggregate-level analysis: Simmering versus sudden conflicts

Conflict episode:		Dependent variable: $Loan_{gsct}$		P -value
		Sudden	Simmering	$diff. = 0$
Foreign $\times$ Conflict	β_1	-2.086*** (0.487)	0.055 (0.230)	0.0001
Foreign $\times$ Conflict $\times$ Military	β_3	4.220*** (0.915)	0.974*** (0.253)	0.0007
Host Region $\times$ Year FE			✓	
Conflict-Type FE			✓	
Conflict Type $\times$ Military FE			✓	
Foreign $\times$ Military FE			✓	
Military $\times$ Year FE			✓	
Foreign $\times$ Year FE			✓	
Foreign $\times$ Host Country FE			✓	
N obs			20,334	
N of Host Region $\times$ Year clusters			229	
Pseudo R^2			0.825	
N conflict episodes		29	43	
N conflict country-years		66	130	
N unclassified episodes/country-years			9/25	

Note: This table estimates a version of equation (7) that distinguishes sudden, simmering, and unclassified conflict episodes in a single pooled regression. An episode is *sudden* if battle-related deaths were below 250 in the year before they crossed the 1,000 threshold, *simmering* if they were already at least 250, and *unclassified* if that year's death count is unavailable. The regression includes separate indicators for each conflict type and their interactions with *Foreign* and *Military*; coefficients for unclassified episodes are not reported. P -value $diff. = 0$ is from a Wald test of equality between the sudden and simmering coefficients. The dependent variable is total lending $Loan_{gsct}$ (billions of US dollars, winsorized at the 99th percentile) by lender origin g to sector s in country c in year t . The estimator is Poisson pseudo-maximum likelihood with high-dimensional fixed effects (Correia et al., 2020). Data are from UCDP and DealScan. Standard errors clustered by host region $\times$ year are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table IA.6. Aggregate-level analysis: Cross-country heterogeneity

		Dependent variable: <i>Loan_{gsct}</i>	
	Capacity:	Public debt	Bank assets
		(1)	(2)
Foreign × Conflict in Low-Capacity Country	β_1^{low}	0.024 (0.324)	-1.627*** (0.463)
Foreign × Conflict in High-Capacity Country	β_1^{high}	-0.961*** (0.350)	0.132 (0.256)
Foreign × Conflict in Low-Capacity Country × Military	β_3^{low}	1.256*** (0.289)	3.585*** (0.738)
Foreign × Conflict in High-Capacity Country × Military	β_3^{high}	2.805*** (0.619)	0.891*** (0.286)
Host region × Year FE		✓	✓
Conflict in Low-Capacity Country × Military FE		✓	✓
Conflict in High-Capacity Country × Military FE		✓	✓
Foreign × Military FE		✓	✓
Military × Year FE		✓	✓
Foreign × Year FE		✓	✓
Foreign × Host Country FE		✓	✓
<i>N</i> obs		11,666	11,526
<i>N</i> of host region × year clusters		229	229
R ² (adj.)		0.786	0.787
<i>N</i> conflict countries in the Low-Capacity Group		7	11
<i>N</i> conflict countries in the High-Capacity Group		9	5
<i>P</i> -value of the linear test: $\beta_1^{low} = \beta_1^{high}$		0.041	0.001
<i>P</i> -value of the linear test: $\beta_1^{low} + \beta_3^{low} = \beta_1^{high} + \beta_3^{high}$		0.292	0.146

Note: This table estimates a version of equation (7) that splits countries by fiscal and domestic financial capacity. Both split variables are averaged within country across all sample years. In column (1), the low-capacity group consists of countries in the upper tercile of *Public debt* (general government gross debt, % of GDP; IMF World Economic Outlook); in column (2), it consists of countries in the bottom tercile of *Bank assets* (banking system assets, % of GDP). The estimator is Poisson Pseudo-Maximum Likelihood with high-dimensional fixed effects (Correia et al., 2020). $Loan_{gsct}$ is total lending (billions of US dollars, winsorized at the 99th percentile) by lender origin g to sector s in country c in year t . *Foreign* equals one for cross-border lending and zero for domestic lending; *Conflict* equals one if the borrower country records at least 1,000 battle-related deaths in a calendar year; *Military* equals one for loans to firms in primary military or dual-use SIC industries (Table IA.2). Host regions are the seven World Bank regions plus a residual category. Data: IMF World Economic Outlook, World Bank (World Development Indicators), UCDP, and DealScan. Standard errors clustered by host region $\times$ year are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Internet Appendix C Loan-level results: further tests

This appendix supports Section 5.2 of the main text. Section C.1 describes the robustness tests for the baseline loan-level results summarized in Section 5.2.4, and Sections C.2 and C.3 report the two extensions summarized in that section: spillovers to neighboring countries and post-conflict dynamics.

C.1 Robustness

We first re-run equation (8) while defining *Conflict* using different casualty thresholds. Our baseline specification, column (5) of Table IA.7, applies a cut-off of at least 1,000 deaths per year. We reconstruct this variable using lower thresholds: 100, 250, 500, or 750 annual deaths (columns (1)–(4)). We find no difference in the response of domestic and cross-border bank lending to civilian firms when *Conflict* is defined using a relatively low threshold (up to 500 battle-related deaths, columns (1)–(3)). It is only when conflicts get more violent (i.e., for a threshold of 750 battle-related deaths) that we start to observe a larger decline in credit by cross-border lenders to civilian 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 that the reallocation coefficient β_3 is positive and significant at every threshold (columns (1)–(5)). The effect is small at the 100-death threshold (0.117) and between 0.409 and 0.563 at thresholds of 250 deaths and above. The civilian retrenchment thus requires intense conflict, whereas the military reallocation is robust to the threshold.

Second, Table IA.8 assesses robustness to missing loan shares and the heterogeneity of syndicates and loan types. Column (1) shows our baseline approach, in which we impute missing shares using each bank’s historical average share from loans with known allocations and then rescale 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), following Wix (2023) (column (5)) and only loans that are

not extended for a takeover or acquisition, following Chakraborty, Goldstein and MacKinlay (2018) (column (6)). In both cases, our results continue to hold.

Table IA.7. Different indicator thresholds

$\mathbb{1}_{\{deaths \geq j\}}$	Dependent variable: $Loan_{bfsc}$				
	$j = 100$	$j = 250$	$j = 500$	$j = 750$	$j = 1,000$
	(1)	(2)	(3)	(4)	(5)
Foreign $\times$ Conflict	0.100 (0.076)	0.133 (0.143)	0.031 (0.134)	-0.260** (0.104)	-0.313*** (0.116)
Foreign $\times$ Conflict $\times$ Military	0.117*** (0.041)	0.433*** (0.093)	0.563*** (0.092)	0.409*** (0.094)	0.523*** (0.105)
Bank FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓	✓	✓
Foreign $\times$ Year FE	✓	✓	✓	✓	✓
N obs	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
R^2 (adj.)	0.867	0.867	0.867	0.867	0.867
N of conflict countries	41	30	25	19	16

Note: This table reports estimates of equation (8) with the natural logarithm of the loan amount as the dependent variable. *Foreign* equals one for cross-border lending and zero for domestic lending. *Military* equals one if the borrower operates in a primary or dual-use military-related SIC industry (see Table IA.2). The *Conflict* indicator is one if the firm's country experiences $\geq 100, 250, 500, 750$, 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 and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table IA.8. Loan composition and syndicate structure

Dependent variable	<i>Loan_{bfsct}</i>					
	Baseline	Equal shares	Lead≤5	Lead≤10	Loan type	Loan purpose
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.313*** (0.116)	-0.164** (0.066)	-0.367*** (0.120)	-0.294** (0.115)	-0.339*** (0.125)	-0.327*** (0.120)
Foreign × Conflict × Military	0.523*** (0.105)	0.489*** (0.084)	0.502*** (0.126)	0.439*** (0.108)	0.556*** (0.104)	0.567*** (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	✓	✓	✓	✓	✓	✓
<i>N</i> obs	1,308,048	1,307,102	1,177,191	1,267,037	899,699	1,201,935
<i>N</i> 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: This table reports estimates of equation (8) under an alternative imputation of loan shares and for restricted loan samples. The dependent variable is the log loan amount. Column (1) reproduces the baseline, which imputes missing loan shares from each bank's historical average share and rescales them to sum to 100%. Column (2) instead splits each loan equally among syndicate members when actual shares are unavailable. Columns (3) and (4) exclude loans with more than five and ten lead arrangers, respectively. Column (5) keeps only term loans and revolving credit lines with a maturity of at least one year, and column (6) drops takeover and acquisition loans. *Foreign* equals one for cross-border lending and zero for domestic lending; *Conflict* equals one if the firm's country experiences at least 1,000 battle-related deaths in a year; *Military* equals one if the firm operates in a primary military or dual-use SIC industry (Table IA.2). Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Third, Table IA.9 checks whether our results are driven by a few source countries. We exclude large and important countries, economically and in terms of creditor numbers. This confirms that our results are not driven by specific countries. We 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)); the UK (6%, column (5)), and China (2.7%, column (6)).

Table IA.9. Excluding lenders from major economies

Dependent variable Excl. banks from	<i>Loan_{bfsct}</i>					
	US	Japan	DE	FR	UK	China
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign $\times$ Conflict	-0.320*** (0.118)	-0.304** (0.118)	-0.305*** (0.117)	-0.315*** (0.119)	-0.346*** (0.120)	-0.323*** (0.118)
Foreign $\times$ Conflict $\times$ Military	0.553*** (0.113)	0.531*** (0.108)	0.494*** (0.107)	0.520*** (0.109)	0.610*** (0.099)	0.542*** (0.108)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓	✓	✓	✓
Foreign $\times$ Year FE	✓	✓	✓	✓	✓	✓
<i>N</i> obs	872,877	1,104,600	1,224,094	1,227,107	1,229,754	1,271,767
<i>N</i> 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: This table excludes all loans, domestic and cross-border, by banks headquartered in the US, Japan, Germany, France, the UK, and China in columns (1), (2), (3), (4), (5), and (6), respectively. The dependent variable is the natural logarithm of the loan amount. *Foreign* equals one for cross-border lending and zero for domestic lending. *Conflict* is a dummy equal to one if the firm's country experienced at least 1,000 battle-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 industry (see Table IA.2 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.

Finally, Table IA.10 shows results for restricted lender samples. Column (2) limits the sample to the most active lenders: those participating in over 300 loan tranches, domestic or cross-border, over 1989–2020. Of these 608 lenders, 575 remain in the estimation sample. The reallocation coefficient remains positive and significant, but because these lenders also retrench more from civilian firms, their net military lending is not above that of domestic banks. Column (3) excludes loans booked through foreign affiliates, so that cross-border lending comes only from lenders' headquarters; β_3 is slightly larger, and the net military effect is positive.

Table IA.10. Different subsamples of lenders

Dependent variable	<i>Loan_{bfsct}</i>		
	Baseline	Most active lenders	Without foreign affiliates
	(1)	(2)	(3)
Foreign $\times$ Conflict	-0.313*** (0.116)	-0.532*** (0.191)	-0.354*** (0.135)
Foreign $\times$ Conflict $\times$ Military	0.523*** (0.105)	0.410** (0.159)	0.605*** (0.121)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓
Foreign $\times$ Year FE	✓	✓	✓
<i>N</i> obs	1,308,048	980,396	1,171,502
<i>N</i> 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: lenders participating in more than 300 loan tranches over 1989–2020, of which 575 remain in the estimation sample (column (2)) and cross-border lenders’ headquarters only (column (3)). The dependent variable is the natural logarithm of the loan amount. *Foreign* equals one for cross-border lending and zero for domestic lending. *Conflict* equals one if the firm’s country had at least 1,000 battle-related deaths in a year, and *Military* equals one if the loan is to a military-related SIC industry (Table IA.2). 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.

C.2 Spillovers to neighboring countries

Wars and other violent conflicts can reshape regional security dynamics (Federle et al., 2026), 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 Table IA.1, excluding cases where neighboring countries themselves experience major conflicts ($\geq 1,000$ battle-related 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.

In Table IA.11, 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 battle-related deaths to zero deaths, isolating pure spillover effects. We find no military–civilian reallocation in cross-border lending to neighbors relative to domestic banks: the triple interaction is small and insignificant in every column. The relative response is thus confined to countries in conflict. Columns (3)–(4) show that cross-border lenders reduce civilian credit to neighbors with few or no battle-related deaths, but without a corresponding reallocation toward military firms.

C.3 Post-conflict dynamics

Our baseline specification treats pre- and post-conflict years equally in the reference category. However, post-conflict years may be distinct, as banks may continue military financing if peace appears fragile. 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 *Post-Conflict* as an indicator equal to one in the first post-conflict year (column (1)), in either of the first two post-conflict years (column (2)), or in any of the first three (column (3)), so that each column estimates the response over a cumulative window. Table IA.12 reports equation (8) with interactions of this indicator with *Foreign* and *Mil-*

Table IA.11. Spillovers to neighboring countries

Neighboring countries:	Dependent variable: $Loan_{bfsc}$			
	Countries with $N\ deaths \leq j$:			
	$j = 1,000$	$j = 500$	$j = 100$	$j = 0$
	(1)	(2)	(3)	(4)
Neighbor $\times$ Foreign	-0.026 (0.038)	-0.050 (0.034)	-0.097*** (0.036)	-0.102*** (0.038)
Neighbor $\times$ Foreign $\times$ Military	0.063 (0.043)	-0.045 (0.042)	-0.020 (0.039)	-0.024 (0.041)
Bank FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓	✓
Foreign $\times$ 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 and zero for domestic lending. *Neighbor* equals one for firms in countries bordering conflict countries. *Military* equals one for primary or dual-use military industries (Table IA.2). All regressions include fixed effects as specified. Data: UCDP and DealScan. ***, **, * denote significance at 1%, 5%, 10%. Standard errors clustered by bank in parentheses.

itary. Since we retain $Conflict \times Foreign \times Military$, the new triple interaction measures changes in cross-border military lending relative to other non-conflict years.

Cross-border lenders' military lending advantage persists over the first post-conflict year (0.796, column (1)) and over the first two years (0.547, column (2)) but is close to zero over the three-year window (0.077, column (3)). Because the windows are cumulative, the drop between columns (2) and (3) reflects a reversal in the third year. Meanwhile, the coefficient on $Post-Conflict \times Foreign$ turns positive and is weakly significant over the three-year window, so cross-border lenders begin to re-enter through civilian lending. The net cross-border military effect remains positive over this window, but by then it reflects the

Table IA.12. Cross-border lending after violent conflicts

Post-conflict period:	Dependent variable: $Loan_{bfset}$		
	One year	Two years	Three years
	(1)	(2)	(3)
Post-Conflict $\times$ Foreign	-0.026 (0.148)	0.098 (0.136)	0.200* (0.118)
Post-Conflict $\times$ Foreign $\times$ Military	0.796*** (0.172)	0.547*** (0.194)	0.077 (0.178)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓
Foreign $\times$ Military FE	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓
Foreign $\times$ 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

Note: Estimates of equation (8) for post-conflict periods. Dependent variable: log loan amount. *Foreign* equals one for cross-border lending and zero for domestic lending. *Post-Conflict* equals one in the first year after a conflict ends (column (1)), in either of the first two post-conflict years (column (2)), or in any of the first three post-conflict years (column (3)), and zero otherwise; a conflict is one with at least 1,000 battle-related deaths in a year, and post-conflict years are years without conflict. *Military* equals one for primary or dual-use military industries (Table IA.2). 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.

civilian recovery rather than a military advantage. These results show that cross-border lenders' military lending advantage is concentrated during active conflicts, when defense demand peaks and domestic financial capacity is constrained. Once conflicts end, cross-border lenders reallocate from military to civilian lending as defense profitability declines and reconstruction opportunities increase.

Internet Appendix D Mechanism: additional evidence

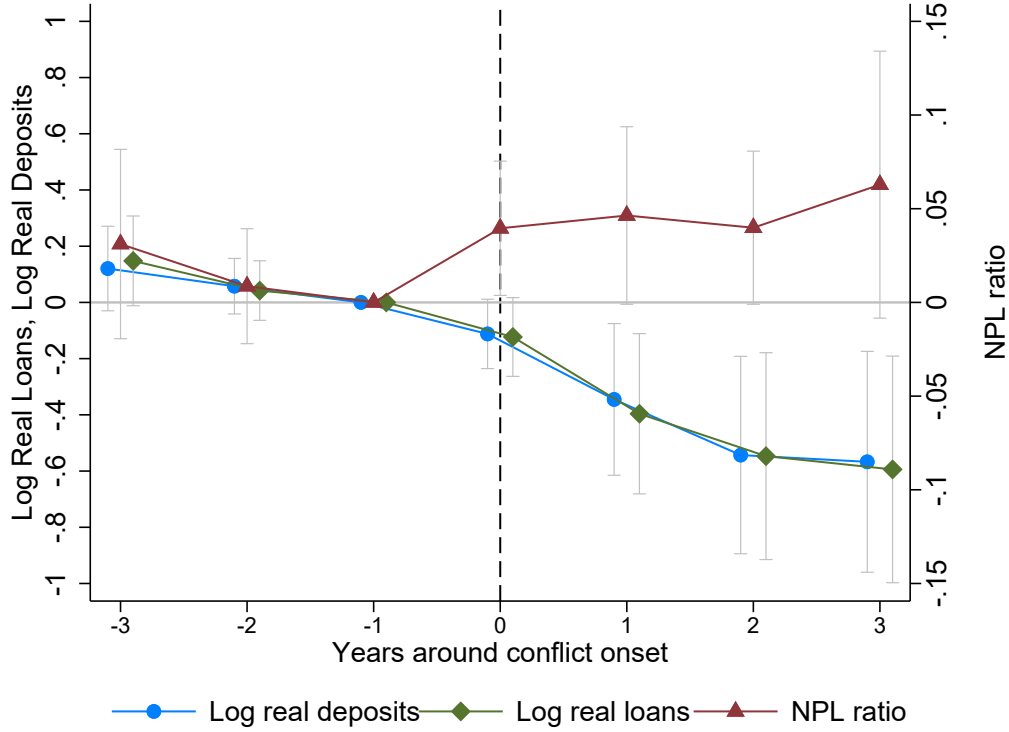
This appendix supports Section 6.3 of the main text. Section D.1 reports cross-country event studies of domestic banking systems around conflict onset, and Section D.2 examines whether cross-border lenders' prior specialization in conflict countries or in the military sector shapes their wartime lending.

D.1 Domestic banking systems around conflict onset

We first examine whether violent conflicts coincide with a deterioration in domestic banking capacity. This exercise complements the main mechanism tests in Section 6.3: if domestic banks become funding-constrained during conflicts, foreign lenders may be better positioned to accommodate the rise in military firms' credit demand. We therefore use public country-level banking data to study the behavior of real bank deposits, real bank loans, and non-performing loans around conflict onset.

For each conflict onset, we construct a stacked event-study panel over a seven-year window from $t - 3$ to $t + 3$. Treated countries are matched to four never-treated control countries using pre-conflict macroeconomic and banking-sector observables averaged over $t - 3$ to $t - 1$ (levels and trends of real deposits, real loans, and real bank assets). Figure IA.6 shows that domestic banking systems weaken sharply after conflict onset. Real deposits and real loans fall persistently relative to matched controls, while NPL ratios rise. This pattern is consistent with a broad contraction in domestic banking capacity during conflicts.

Figure IA.6. Domestic banking systems around conflict onset



Note: This figure reports matched country-level event-study estimates for domestic banking-system conditions around conflict onset. For each conflict onset, we match the treated country to four never-treated control countries using pre-conflict observables averaged over $t-3$ to $t-1$: log real GDP, log population, log real bank deposits, log real bank loans, log real bank assets, and pre-conflict trends in real deposits, real loans, and real bank assets. We estimate

$$Y_{iect} = \sum_{\tau \neq -1} \beta_{\tau} (Treated_{ie} \times \mathbf{1}\{\tau\}) + \alpha_{ie} + \delta_{e\tau} + \varepsilon_{iect},$$

where i indexes countries, e indexes conflict episodes, c denotes the matched country set, and τ is event time relative to conflict onset. Coefficients for log real deposits and log real loans are in log points. NPL coefficients are in ratio units (a coefficient of 0.06 corresponds to a 6 percentage-point increase). $Treated_{ie}$ equals one for the conflict country in each matched set and zero for matched non-conflict countries. The omitted period is the last pre-conflict year, $\tau = -1$. The fixed effect α_{ie} absorbs country-within-event differences, while $\delta_{e\tau}$ absorbs shocks common to all countries in the same event and relative year. Standard errors are two-way clustered by country and conflict episode. The dashed vertical line marks the onset of conflict. The left axis reports coefficients for log real deposits and log real loans; the right axis reports the NPL ratio. The underlying World Bank Global Financial Development Database variables are bank deposits, bank private credit, bank assets, and banks' non-performing loans to gross loans. Nominal deposits, loans, and bank assets are deflated using country-specific CPI before taking logs. Capped bars report 95% confidence intervals.

D.2 Bank specialization

A recent literature documents large differences in lending specialization across banks (Paravisini, Rappoport and Schnabl, 2023; Blickle, Parlatore and Saunders, 2026; 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 the military sector.

To investigate this, we measure a lender's military specialization before conflict. For each conflict destination, the relative pre-conflict share is the lender's average share of military lending in its syndicated lending in the years before the destination's first conflict onset. The excess share subtracts the military sector's contemporaneous share of global syndicated lending before taking the same average. Both measures are mean-centered. Table IA.13 estimates a pooled version of equation (8) in which $Foreign \times Conflict \times Military$ is interacted with specialization. The military response is positive and significant at both the 25th and the 75th percentiles of the pre-conflict share (0.482 and 0.543 under the relative measure), and the difference between the two is small and insignificant. The military reallocation is therefore not driven by lenders that were already specialized in the sector: cross-border lenders that were less specialized in military lending before the conflict expand it about as much as those that were more specialized.

Table IA.13. Predetermined military-sector specialization and cross-border lending during conflicts

	Relative pre-conflict share (1)	Excess pre-conflict share (2)
Foreign $\times$ Conflict $\times$ Military at mean specialization	0.524*** (0.109)	0.524*** (0.109)
Specialization $\times$ Conflict $\times$ Military	-0.148 (0.411)	-0.184 (0.410)
Foreign $\times$ Specialization $\times$ Conflict $\times$ Military	0.299 (0.580)	0.321 (0.587)
β_3 at P25 specialization	0.482*** (0.151)	0.482*** (0.147)
β_3 at P75 specialization	0.543*** (0.106)	0.543*** (0.107)
<i>Difference: P75 – P25</i>	0.061 (0.118)	0.062 (0.112)
<i>P-value: P75 = P25</i>	0.606	0.580
Bank FE, Firm FE	✓	✓
Home Country $\times$ Year FE	✓	✓
Host Country $\times$ Year FE	✓	✓
Conflict $\times$ Military FE	✓	✓
Foreign $\times$ Military FE	✓	✓
Military $\times$ Year FE	✓	✓
Foreign $\times$ Year FE	✓	✓
<i>N</i> obs.	1,308,048	1,308,048
<i>N</i> banks	14,021	14,021
R ² (adj.)	0.867	0.867

Note: This table estimates a pooled version of equation (8) in which the conflict-time response varies continuously with lenders' predetermined military-sector specialization. For each conflict destination, the relative pre-conflict share is the lender's average military share of syndicated lending observed before the destination's first conflict onset. The excess share subtracts the military sector's contemporaneous share of global syndicated lending before taking the same pre-conflict average. For lender–destination pairs without an observed pre-conflict history, specialization is measured from the lender's available lending history. Both measures are mean-centered. The rows labeled β_3 at P25 and P75 report linear combinations of the *Foreign $\times$ Conflict $\times$ Military* coefficient and its interaction with specialization, evaluated at the 25th and 75th percentiles of specialization. The difference row tests whether the implied military response differs across these percentiles. The dependent variable is the natural logarithm of the loan amount. All regressions include the fixed effects shown. Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Internet Appendix E Geopolitical alignment: details

This appendix supports Section 7 of the main text. Section E.1 documents the assignment of lender and borrower countries to UN-voting blocs and the dyadic support behind the estimates in Table 6. Section E.2 pools the dyads into aligned and non-aligned lending, compares the two groups directly within the same destination, and re-estimates the dyadic specification with alternative bloc definitions. Section E.3 compares the responses of banks and non-banks and of state-owned and private banks.

E.1 Bloc assignment and dyadic support

Table IA.14 lists the countries in each bloc under the baseline $t - 1$ rule, together with the assignment rules for territories and non-UN entities. Table IA.15 lists the conflict borrower countries in the dyad sample by bloc and conflict year, and Table IA.16 reports the number of observations, banks, and countries in each of the nine lender–borrower dyads.

Table IA.14. Country composition of geopolitical blocs

Bloc	Countries (modal assignment under the $t - 1$ rule, 1989–2020)
West (49)	Albania; Andorra; Australia; Austria; Belgium; Bosnia & Herzeg.; Bulgaria; Canada; Croatia; Czechia; Czechoslovakia [†] ; Denmark; Estonia; Finland; France; Georgia; German Fed. Rep.; Germany; Greece; Hungary; Iceland; Ireland; Israel; Italy; Japan; Latvia; Liechtenstein; Lithuania; Luxembourg; Marshall Islands; Micronesia; Moldova; Monaco; Montenegro; Netherlands; North Macedonia; Norway; Palau; Poland; Portugal; Romania; San Marino; Slovakia; Slovenia; Spain; Sweden; Switzerland; UK; US
East (23)	Afghanistan; Antigua & Barbuda; Brunei [†] ; Cambodia; China; Congo, Dem. Rep.; Gabon; India; Jordan [†] ; Lesotho; Mali; Morocco; Mozambique; Namibia; Niger; Pakistan; St. Kitts & Nevis; São Tomé & Príncipe; Senegal [†] ; Seychelles [†] ; Sri Lanka; St. Lucia; UAE
Neutral (125)	All other countries with UN voting records.

Note: This table lists countries by their modal geopolitical bloc over 1989–2020. Annual blocs are constructed from UN General Assembly ideal points (Bailey et al., 2017), with the United States as the West anchor and China (Russia before China enters the sample) as the East anchor. Under the $t - 1$ rule, a country is assigned in year t to the bloc it occupied in $t - 1$. Because these are modal assignments, the totals need not match the year-specific country counts in the dyad sample. Territories inherit the bloc of the relevant metropole: Bermuda, British Virgin Islands, Cayman Islands, and Gibraltar are mapped to the United Kingdom; Guadeloupe to France; Netherlands Antilles to the Netherlands; Hong Kong to the United Kingdom through 1997 and to China from 1998 onward; and Macau to Portugal through 1999 and to China from 2000 onward. Taiwan and Kosovo are assigned to the West, Palestine to the East, and Serbia to the Neutral bloc.

Table IA.15. Conflict borrower countries by time-varying UN-voting bloc

West		Neutral		East	
Country	Conflict years	Country	Conflict years	Country	Conflict years
Israel	2014	Algeria	1999	Algeria	1998
Russia	1995–1996	Angola	1998, 2001	Angola	1999
Turkey	1992, 1994	Colombia	1994, 1996, 1999–2005	Congo, DR	2013
Ukraine	2014–2015	Congo, DR	2014	India	1993–1994, 2000–2002, 2008–2010
		India	1989–1991, 1999, 2003–2007	Iraq	2008–2009, 2011
		Iraq	2005–2006, 2016–2017	Nigeria	2013, 2015, 2018–2020
		Nigeria	2014, 2016–2017	Pakistan	2008–2015
		Philippines	1991, 2017	Philippines	1990, 2000, 2003
		Russia	1999–2000, 2002, 2004	Sri Lanka	1995–1998, 2000–2001, 2006–2008
		Sri Lanka	1999, 2009		
		Turkey	1993, 1995–1999, 2016		

Note: This table lists the conflict-borrower countries that appear in the foreign-loan geopolitical-dyad sample and shows the conflict years in which each borrower is classified as West, Neutral, or East. The baseline assignment uses the UN-voting bloc at $t - 1$. When a sovereign country's lagged UN observation is unavailable in a given year, we use its current-year UN bloc. For a narrow set of non-UN territories, we inherit the metropole's bloc (for example, Hong Kong from the United Kingdom before 1998 and from China thereafter). The remaining non-UN political entities are assigned by explicit fallback rules: Taiwan and Kosovo are coded West, Palestine East, and Serbia Neutral.

Table IA.16. Dyadic support for time-varying UN-voting blocs

Dyad	Obs.	Share (%)	Banks	Lender countries	All host countries	Conflict host countries
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Full foreign-loan sample</i>						
West-West	368,061	60.67	5,225	50	57	4
West-Neutral	84,406	13.91	3,429	47	123	11
West-East	48,359	7.97	2,656	35	94	8
Neutral-West	32,944	5.43	1,325	73	50	4
Neutral-Neutral	13,854	2.28	1,235	70	111	10
Neutral-East	11,230	1.85	1,025	63	86	8
East-West	25,975	4.28	901	48	45	3
East-Neutral	9,587	1.58	786	54	104	9
East-East	12,235	2.02	859	53	83	7
<i>Panel B: Borrower-country war years</i>						
West-West	320	3.09	171	26	4	4
West-Neutral	6,231	60.09	759	37	11	11
West-East	1,425	13.74	399	23	8	8
Neutral-West	28	0.27	24	10	4	4
Neutral-Neutral	803	7.74	180	39	10	10
Neutral-East	488	4.71	172	29	8	8
East-West	12	0.12	8	7	3	3
East-Neutral	720	6.94	146	26	9	9
East-East	343	3.31	133	23	7	7

Note: This table reports dyadic support for the foreign-loan geopolitical specification under the rebuilt time-varying UN-voting blocs. Countries are assigned to West, Neutral, and East primarily using the rebuilt UN bloc at $t - 1$, with current-year rebuilt UN blocs used only when the lagged sovereign observation is unavailable. A narrow fallback covers non-UN territories and special political entities: territories inherit the bloc of the relevant metropole, while Taiwan and Kosovo are coded West, Palestine East, and Serbia Neutral. Country counts are harmonized at the sovereign/metropole level, so mapped territories are not counted separately from the sovereign country whose bloc they inherit. Panel A reports support in the full foreign-loan regression sample. Panel B restricts the same sample to borrower-country years with at least 1,000 battle-related deaths; lender countries are not restricted by their own conflict status. Share (%) reports each dyad's share in total foreign-loan observations within the corresponding panel. Conflict host countries counts unique borrowing countries that experience at least one year with at least 1,000 battle-related deaths in the sample.

E.2 Alignment tests and alternative bloc definitions

Table IA.17 pools the Western and Eastern dyads into aligned and non-aligned lending and tests the difference between the two.

Table IA.17. Geopolitical alignment and cross-border lending during violent conflicts

	Dependent variable: $Loan_{bfsc}$		
	Aligned foreign vs. domestic (1)	Non-aligned foreign vs. domestic (2)	Non-aligned minus aligned (3)
Conflict $\times$ Foreign group	-0.161 (0.140)	-0.141 (0.131)	0.020 (0.093)
Conflict $\times$ Military $\times$ Foreign group	-0.078 (0.208)	0.634*** (0.199)	0.712*** (0.257)
<i>Net military effect</i>	-0.239 (0.233)	0.493** (0.236)	0.732*** (0.248)
Other classified foreign-group interactions		✓	
Bank FE, Firm FE		✓	
Home Country $\times$ Year FE		✓	
Host Country $\times$ Year FE		✓	
Foreign Group $\times$ Military FE		✓	
Conflict $\times$ Military FE		✓	
Military $\times$ Year FE		✓	
Foreign Group $\times$ Year FE		✓	
N obs.		1,299,029	
N lenders		13,966	
R^2 (adj.)		0.868	

Note: This table reports a single pooled loan-level regression that summarizes the directional dyads in Table 6. The dependent variable is the log loan amount. *Conflict* equals one if the borrower's country experiences at least 1,000 battle-related deaths in a year; *Military* equals one if the borrower operates in a primary military or dual-use SIC industry. Countries are assigned to West, Neutral, and East blocs by their UN-voting bloc in $t - 1$ (Section 7). *Aligned foreign* comprises West-to-West and East-to-East cross-border loans; *Non-aligned foreign* comprises West-to-East and East-to-West cross-border loans. Dyads involving a Neutral country form a separate group whose coefficients are not reported, and domestic loans are the omitted category. Columns (1) and (2) report aligned and non-aligned foreign lending relative to domestic lending, and column (3) the difference between them. *Net military effect* is the sum of the coefficients on *Conflict* $\times$ *Foreign group* and *Conflict* $\times$ *Military* $\times$ *Foreign group*. Data are from UCDP, DealScan, and Bailey et al. (2017). Standard errors clustered by lender are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table IA.18 compares aligned and non-aligned cross-border lenders directly, within the same host country $\times$ sector $\times$ year cell, so that both face the same destination-specific credit demand. In all four specifications, neither the civilian nor the net military response differs significantly between the two groups of lenders.

Table IA.18. Aligned versus non-aligned cross-border lenders: Direct comparison

	Dependent variable: $Loan_{bfsc}$			
	Preferred support (1)	All West–East dyads (2)	Same firm-year (3)	Three-bloc version (4)
Conflict $\times$ Aligned, β_1	0.005 (0.131)	0.016 (0.131)	-0.039 (0.110)	-0.002 (0.056)
Conflict $\times$ Military $\times$ Aligned, β_3	0.023 (0.247)	0.054 (0.281)	-0.012 (0.212)	-0.019 (0.099)
<i>Net military effect: $\beta_1 + \beta_3$</i>	<i>0.028 (0.270)</i>	<i>0.070 (0.308)</i>	<i>-0.051 (0.237)</i>	<i>-0.021 (0.101)</i>
<i>p-value: $\beta_1 + \beta_3 = 0$</i>	<i>0.917</i>	<i>0.820</i>	<i>0.830</i>	<i>0.837</i>
Lender FE	✓	✓	✓	✓
Firm FE	✓	✓		✓
Firm $\times$ Year FE			✓	
Home Country $\times$ Year FE	✓	✓	✓	✓
Host Country $\times$ Military $\times$ Year FE	✓	✓		✓
Alignment $\times$ Host Country FE	✓	✓	✓	✓
Alignment $\times$ Military FE	✓	✓	✓	✓
Alignment $\times$ Year FE	✓	✓	✓	✓
<i>N obs.</i>	406,997	437,060	140,895	572,177
<i>N lenders</i>	4,933	5,149	3,377	6,479
<i>R² (adj.)</i>	0.735	0.733	0.807	0.729
<i>Support in conflict $\times$ military cells (aligned/non-aligned)</i>				
<i>N loan observations</i>	27/140	54/184	27/63	131/795
<i>N identifying cells</i>	14/14	16/20	17/17	27/27
<i>N lender countries</i>	8/13	16/13	8/9	25/38
<i>N conflict host countries</i>	5/5	7/6	5/5	9/9

Note: The sample contains cross-border loans only. Non-aligned lending is the omitted category, so β_1 and β_3 measure aligned-minus-non-aligned differences. Blocs follow the $t - 1$ UN-voting classification (Section 7.1). In columns (1)–(3), aligned lending is West-to-West or East-to-East and non-aligned lending is West-to-East or East-to-West; column (4) adds Neutral countries and compares same-bloc with different-bloc lending. Columns (1) and (4) keep host country $\times$ military $\times$ year cells with both lender types, column (2) keeps all West–East dyads, and column (3) keeps firm-years financed by both types. Identifying cells are host country $\times$ military $\times$ year cells, except in column (3), where they are firm-years. The dependent variable is the log loan amount; *Conflict* and *Military* are defined as in Table 6. Data are from UCDP, DealScan, and Bailey et al. (2017). Standard errors clustered by lender are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table IA.19 replaces the UN-voting blocs with NATO, BRICS, and Rest blocs.

Table IA.19. Within-bloc and cross-bloc lending during violent conflicts

	Dependent variable: $Loan_{bfsc}$		
Country bloc dyad B_{i1} :	<i>NATO</i> to <i>NATO</i>	<i>Rest</i> to <i>NATO</i>	<i>BRICS</i> to <i>NATO</i>
Country bloc dyad B_{i2} :	<i>NATO</i> to <i>Rest</i>	<i>Rest</i> to <i>Rest</i>	<i>BRICS</i> to <i>Rest</i>
Country bloc dyad B_{i3} :	<i>NATO</i> to <i>BRICS</i>	<i>Rest</i> to <i>BRICS</i>	<i>BRICS</i> to <i>BRICS</i>
	$i = 1$	$i = 2$	$i = 3$
Conflict $\times B_{i1}$ Foreign	-0.380*** (0.116)	-0.088 (0.116)	-0.286* (0.160)
Conflict $\times B_{i2}$ Foreign	-0.011 (0.124)	-0.305** (0.142)	-0.242 (0.149)
Conflict $\times B_{i3}$ Foreign	-0.264** (0.123)	-0.306** (0.119)	-0.411*** (0.137)
Conflict $\times$ Military $\times B_{i1}$ Foreign	0.063 (0.148)	0.359** (0.178)	1.824*** (0.358)
Conflict $\times$ Military $\times B_{i2}$ Foreign	-0.175 (0.210)	0.347 (0.293)	0.301 (0.323)
Conflict $\times$ Military $\times B_{i3}$ Foreign	0.575*** (0.133)	0.728*** (0.106)	0.307 (0.213)
Other foreign origin groups	Rest, BRICS	NATO, BRICS	NATO, Rest
Bank FE, Firm FE	✓	✓	✓
Home Country $\times$ Year FE	✓	✓	✓
Host Country $\times$ Year FE	✓	✓	✓
Conflict $\times$ Military FE	✓	✓	✓
Foreign Dyad $\times$ Military FE	✓	✓	✓
Military $\times$ Year FE	✓	✓	✓
Foreign Dyad $\times$ Year FE	✓	✓	✓
N home/(conflict) host countries in dyad bloc B_{i1}	20/1	32/1	5/1
N home/(conflict) host countries in dyad bloc B_{i2}	15/12	40/12	5/7
N home/(conflict) host countries in dyad bloc B_{i3}	23/2	34/2	4/2
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

Note: The dependent variable is the log loan amount. *Conflict* equals one if the firm's country experiences at least 1,000 battle-related deaths in a year; *Military* equals one if the firm operates in a primary military or dual-use SIC industry (Table IA.2). This table replaces the UN-voting blocs in Table 6 with time-invariant NATO, BRICS, and Rest blocs on both the lender and borrower sides, where Rest comprises countries in neither NATO nor BRICS. B_{ij} *Foreign* are nine dummies equal to one if a cross-border lender from bloc i lends to a firm in bloc j ($i, j = 1, 2, 3$ for NATO, Rest, and BRICS); domestic loans are the omitted category. Columns correspond to the origin bloc i and rows to the destination bloc j . Data are from UCDP and DealScan. Standard errors clustered by bank are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

E.3 Lender type and bank ownership

We finally examine heterogeneity across lender types and ownership structures. We classify cross-border lenders as banks or non-banks following Aldasoro et al. (2025). Under this classification, non-bank lenders account for 7.3% of cross-border observations in the estimation sample. The expected differences between banks and non-banks are ambiguous: banks have deeper internal capital markets that facilitate resource reallocation but face stricter regulations that may constrain military lending in conflict zones. Bank ownership represents another important dimension. An extensive literature shows that public and private banks exhibit distinct lending patterns because of political influence (Bircan and Saka, 2021; Koetter and Popov, 2021). If political incentives drive military lending, state-owned banks may respond more strongly to these pressures, potentially explaining our findings on the behavior of cross-border lenders (Section 7).

Table IA.20 analyzes both dimensions. Column (1) shows that banks and non-banks reallocate toward military firms by similar magnitudes; the difference between their reallocation coefficients is statistically insignificant. Banks, however, exhibit a significantly stronger flight-home effect in civilian lending ($p = 0.004$), so the net military effect is larger for non-banks (0.428 versus 0.205). Column (2) shows that both private and state-owned banks reduce civilian lending while reallocating toward military firms during conflicts, with no significant differences between the two ownership groups and similar net military effects (0.321 and 0.305). The similarity of the military reallocation across lender types and ownership structures is more consistent with common commercial incentives than with reallocation driven specifically by government ownership or political directives.

Table IA.20. The role of lender type and bank ownership

		Dependent variable: $Loan_{bfsc}$	
		Foreign bank	Foreign private
	$\mathbf{X}_{1,bft}$ $\mathbf{X}_{2,bft}$	Foreign non-bank	Foreign state-owned
		(1)	(2)
Conflict $\times \mathbf{X}_{1,bft}$	β_{11}	-0.317*** (0.116)	-0.223** (0.094)
Conflict $\times \mathbf{X}_{2,bft}$	β_{12}	-0.047 (0.141)	-0.230** (0.094)
Conflict $\times$ Military $\times \mathbf{X}_{1,bft}$	β_{21}	0.522*** (0.104)	0.544*** (0.126)
Conflict $\times$ Military $\times \mathbf{X}_{2,bft}$	β_{22}	0.475* (0.248)	0.535*** (0.111)
Bank FE		✓	✓
Firm FE		✓	✓
Home Country $\times$ Year FE		✓	✓
Host Country $\times$ Year FE		✓	✓
Conflict $\times$ Military FE		✓	✓
$\mathbf{X}_{k,bft} \times$ Military FE		✓	✓
Military $\times$ Year FE		✓	✓
$\mathbf{X}_{k,bft} \times$ 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 $\mathbf{X}_{2,bft}$ in cross-border obs.		7.3%	8.0%
P -value: $\beta_{11} = \beta_{12}$		0.004	0.887
P -value: $\beta_{21} = \beta_{22}$		0.838	0.930

Note: The dependent variable is the log loan amount. Column (1) compares foreign banks ($\mathbf{X}_{1,bft}$) with foreign non-bank lenders ($\mathbf{X}_{2,bft}$), classified following Aldasoro et al. (2025); column (2) compares foreign private banks with foreign state-owned banks. The $\mathbf{X}_{k,bft} \times$ Military and $\mathbf{X}_{k,bft} \times$ Year fixed effects are estimated separately for each lender group ($k = 1, 2$). The p -values test equality of the corresponding coefficients within each column. *Conflict* equals one if the firm's country experiences at least 1,000 battle-related deaths in a year; *Military* equals one for firms in primary or dual-use military SIC industries (Table IA.2). Data: UCDP and DealScan. Standard errors clustered by lender in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.