Violent Conflict and Cross-Border Lending

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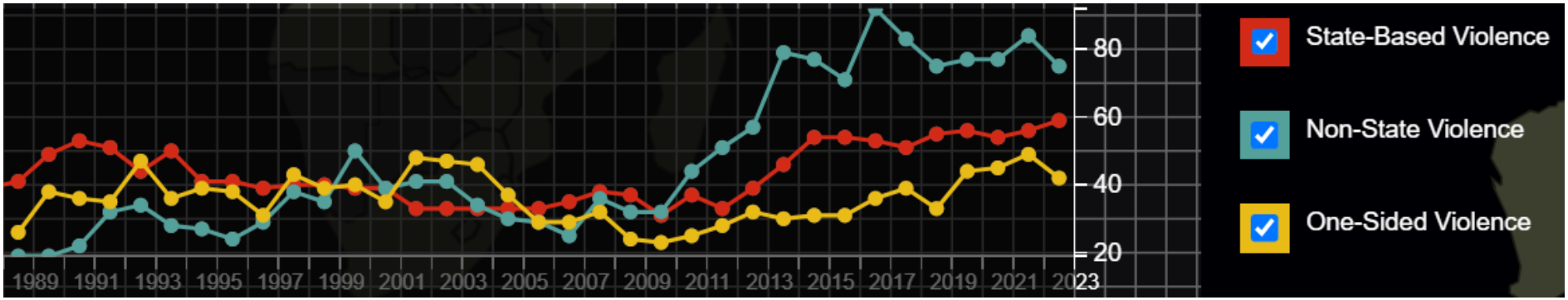
Views are those of the authors, not necessarily those of Deutsche Bundesbank, EBRD, ECB, or the Eurosystem.

A global rise in violent conflicts



Data source: Uppsala Conflict Data Program.

- Ongoing armed conflicts, rising geopolitical tensions, and shifting power dynamics seem to challenge the idea that violence is in long-term decline

  Caldara and Iacoviello 2022 AER; Pinker 2011

- Data confirm an increase in violent conflicts with high human and economic costs

  Armed Conflict Survey 2024, IISS; Armed Conflict Data Project; Uppsala Conflict Data Program

What we (don't yet) know

- Violent conflicts are extremely costly, especially to low-income countries, and access to funding can make or break military success

  Federle, Rohner, and Schularick 2025

- Role for sovereign bond funding and government-to-government lending DiGiuseppe 2015; Zielinski 2016; Horn, Reinhart, and Trebesch 2020

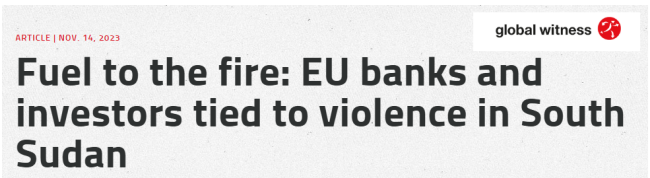
- We know little about how cross-border credit responds to violent conflict, either in the aggregate or across sectors

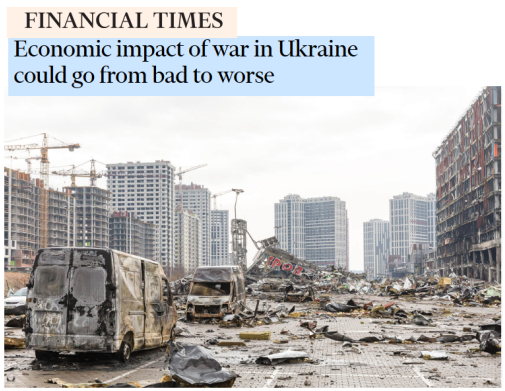
  Longo, Meggiolaro, and Felipe 2024

Banks finance military-related firms, in peacetime and in war

- Financial institutions provided $1 tn to the defense industry globally in 2020–2022
  Longo et al. (2024)

- Europe's 15 largest banks invested €88 bn in arms companies selling to conflict zones
  Oudes et al. (2022)





This paper

- Examine the relationship between private finance and violent conflict through the lens of cross-border bank lending
- Leverage data on 1.3 million syndicated loans by 14k banks to 97k firms in 179 countries (1989–2020)
- Disentangle credit supply from demand across military and non-military sectors

Contribution to the literature

1. **Shock transmission through cross-border syndicated lending**

   Cetorelli and Goldberg 2011; Giannetti and Laeven 2012; De Haas and Van Horen 2013

   $\rightarrow$ We uncover a dual response to violent conflict: cross-border lenders retrench overall yet simultaneously reallocate credit toward defense-related sectors

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   Horn, Reinhart, and Trebesch 2020; Federle, Rohner, and Schularick 2025

   → We show that public *and* private cross-border capital finances conflicts

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3. **Financial repercussions of geopolitical fragmentation**

   Kempf et al. 2023; Chupilkin et al. 2024; Gopinath et al. 2025; Niepmann and Shen 2025

   → We document that military credit reallocation concentrates in politically distant or non-aligned conflict zones

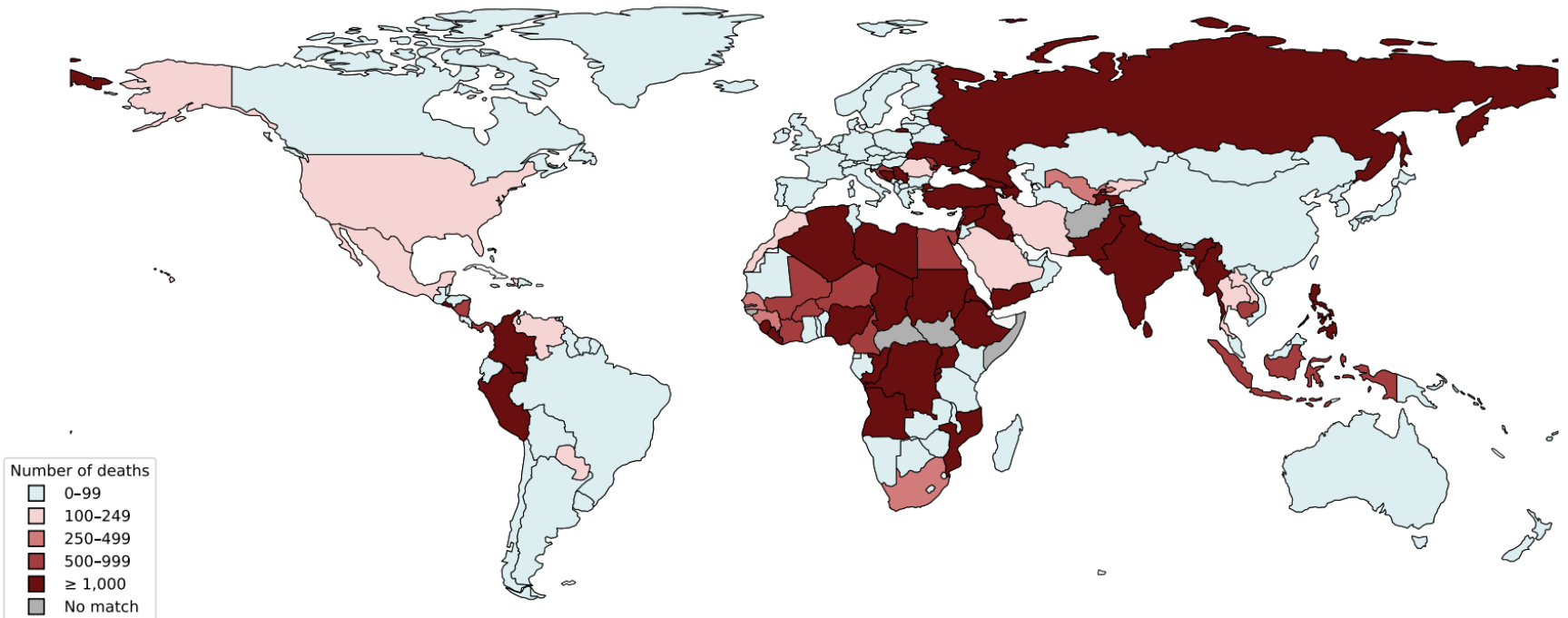
Data

Main data sources

- **Uppsala Conflict Data Program (UCDP)**
  - State-based armed conflicts (at least one party is a state) resulting in $\geq 1k$ battle-related fatalities in a year
- **DealScan**
  - Data on syndicated loans
  - Split each loan into syndicate member shares
  - Aggregation of loan amounts to the bank-firm-year level
- **Compustat**
  - Firm-level data (balance sheets / income statements)

Violent conflicts

Conflict countries by annual battlefield deaths



Note: This figure maps 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. The nature and timing of each conflict is described in Appendix Table A.I. Data sources: Uppsala Conflict Data Program and DealScan.

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- **UK Strategic Export Control List**
  - List of primary military & dual-use items requiring an export authorization (Department for Business and Trade)

Conflict example

Defining military sectors

- Distinguish between firms in 'primary military' and 'dual-use' sectors
- Primary military: From the UK's Military List, we collect key terms such as 'weapon', 'artillery', 'tank', 'bomb', 'missile', 'explosives', etc.
- We then identify all 4-digit SIC codes on the NAICS/SIC website that mention these goods. This yields 10 primary military SIC codes

Primary military sectors

Panel A: Primary military-related sectors

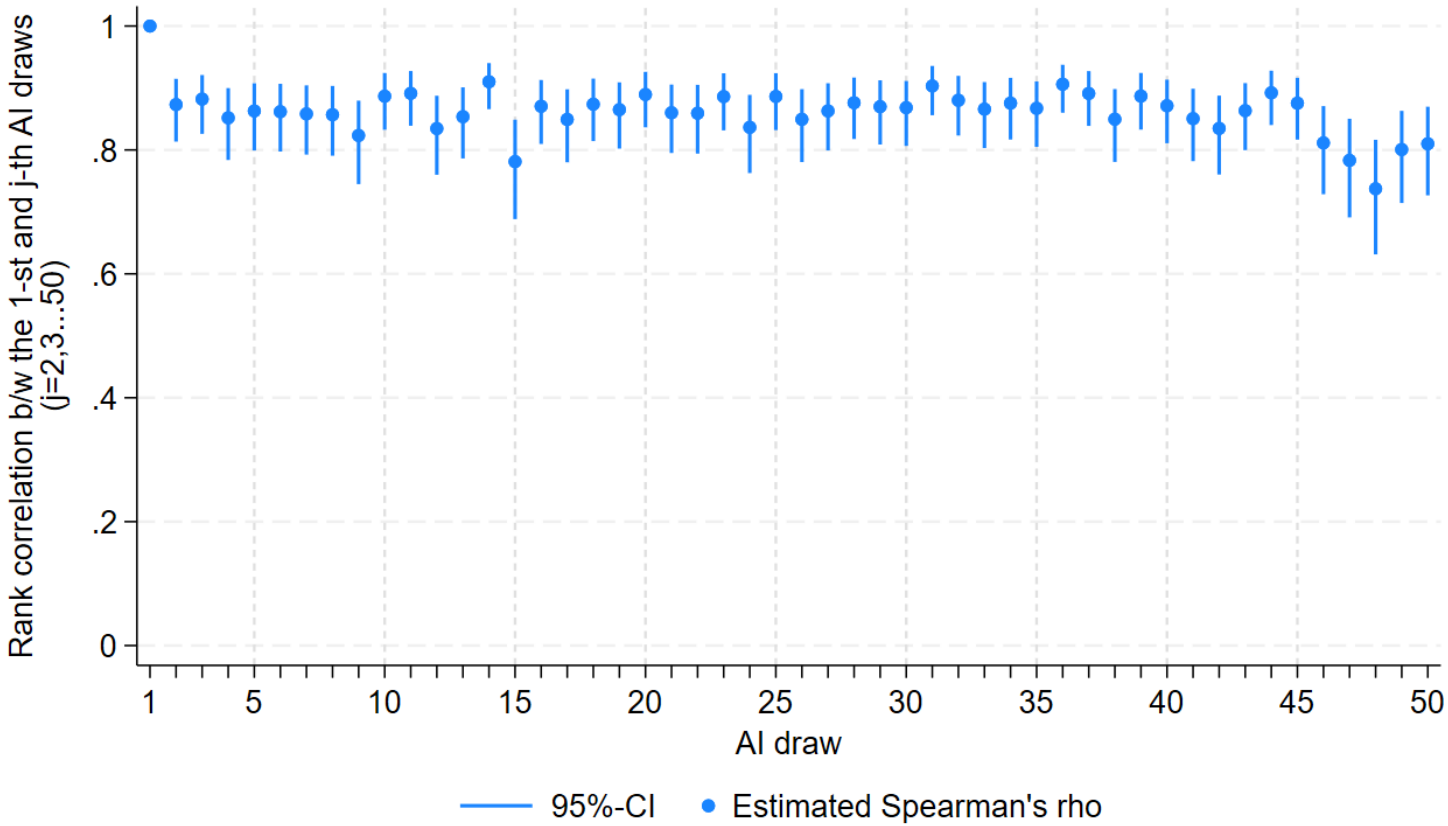
SIC Code	Description
2892	Explosives
3482	Small Arms Ammunition
3483	Ammunition, Except for Small Arms
3484	Small Arms
3489	Ordnance and Accessories, Not Elsewhere Classified
3761	Guided Missiles and Space Vehicles
3764	Guided Missile & Space Vehicle Propulsion Units and Propulsion Unit Parts
3769	Guided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

Defining dual-use sectors

- Extract keywords from the UK's dual-use category titles (e.g., 'nuclear' and 'aircraft'). Find these terms on the NAICS/SIC website: generates **115** potential dual-use SIC codes

- Ask ChatGPT-4o for the probability of military production involvement for the **10** primary military plus **115** dual-use sectors
  - 50 iterations, randomly reordering the 125 SIC codes each time, and calculating the average probability for each sector
  - Retain 79 dual-use sectors $\geq$ 50% average military-use probability

Spearman rank correlation between 1st and jth AI draw



Dual-use sectors

SIC Code	Description	AI Likelihood
3674	Semiconductors and Related Devices	80
2836	Biological Products, Except Diagnostic Substances	60
4499	Water Transportation Services, Not Elsewhere Classified	30
3484	Small Arms	100
2899	Chemicals and Chemical Preparations, Not Elsewhere Classified	70
5734	Computer and Computer Software Stores	40
2829	Explosives	100
4899	Communications Services, Not Elsewhere Classified	60
3462	Iron and Steel Forgings	50
3482	Small Arms Ammunition	100
...		

Example

- In 2015, 15 global banks provided a syndicated loan to the telecommunications company INT Towers in Nigeria
- Parent company then donated an Information Communication Technology Center to the 6th Division of the Nigerian Army

Aggregate-level analysis

Empirical setup: Aggregate-level analysis

- Foreign *vs.* domestic bank lending to military *vs.* non-military sectors during violent conflicts *vs.* non-conflict times:

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

- Poisson Pseudo-ML HD-FE estimator (Correia, Guimaraes, and Zylkin 2020)

Hypotheses

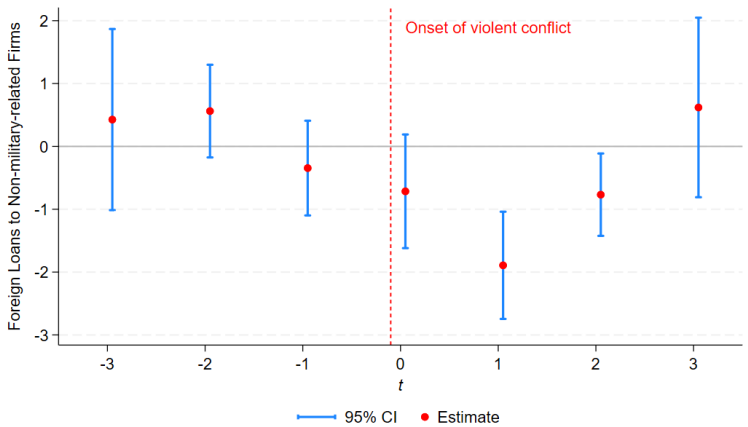
- $\beta_1 < 0$: foreign lenders shrink credit to non-militaries during conflicts
- $\beta_1 + \beta_3 > 0$: foreign lenders strategically expand credit to militaries during conflicts

Aggregate-level baseline results

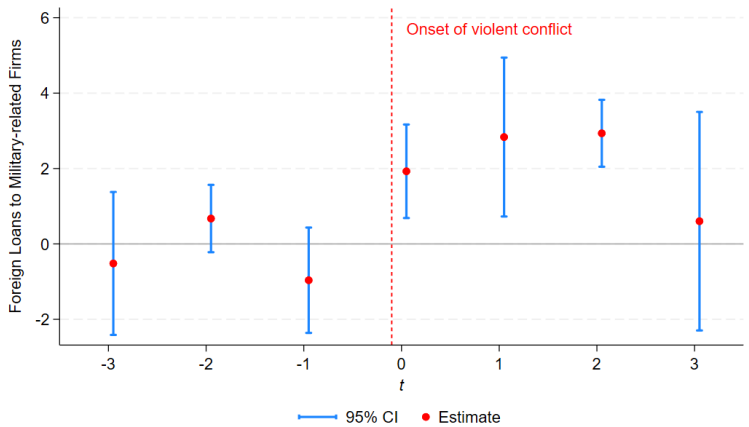
		Dependent variable: $Loan_{gsct}$			
		(1)	(2)	(3)	(4)
Foreign	β_0	0.623***	0.647***		
		(0.035)	(0.033)		
Foreign × Conflict	β_1	0.333	0.166	-0.570*	-0.627**
		(0.353)	(0.363)	(0.325)	(0.317)
Foreign × Military	β_2		-0.096*		
			(0.050)		
Foreign × Conflict × Military	β_3		1.596***	1.596***	1.574***
			(0.390)	(0.390)	(0.387)
Conflict		✓	✓	✓	✓
Host Region × Year FE		✓	✓	✓	✓
Conflict × Military FE			✓	✓	✓
Foreign × Military FE				✓	✓
Foreign × Host Country FE				✓	✓
Military × Year FE					✓
Foreign × Year FE					✓
N obs		22,624	22,624	20,334	20,334
N of Host Region × Year clusters		229	229	229	229
R^2 (adj.)		0.377	0.428	0.822	0.824
Linear test: $\beta_1 + \beta_3 = 0$			*1.761***	*1.026***	*0.946***
			(0.211)	*(0.240)*	*(0.228)*

- Foreign banks cut **non-military lending** 47% more than domestic banks during conflicts
- Foreign banks expand **military lending** 158% more than domestic banks during conflicts

Event study



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



(b) β_3: Foreign Lending to Military Sectors

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

Loan-level analysis

Empirical setup: Loan-level analysis

- Military *vs.* non-military lending by foreign *vs.* domestic banks during violent conflicts *vs.* non-conflict times:

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

Hypotheses:

- $\beta_1 < 0$: foreign lenders shrink credit to non-militaries during conflicts
- $\beta_1 + \beta_3 > 0$: foreign lenders expand credit to militaries during conflicts

Loan-level baseline results

Dependent variable	$Loan_{bfsct}$		
	(1)	(2)	(3)
Foreign	-0.083***	-0.089***	
	(0.010)	(0.010)	
Foreign × Conflict	-0.226*	-0.322***	-0.313***
	(0.117)	(0.117)	(0.116)
Foreign × Military		0.027***	
		(0.008)	
Foreign × Conflict × Military		0.509***	0.523***
		(0.105)	(0.105)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Foreign × Military FE			✓
Military × Year FE			✓
Foreign × Year FE			✓
N obs	1,308,048	1,308,048	1,308,048
N of banks	14,021	14,021	14,021
R^2 (adj.)	0.864	0.866	0.867

- Foreign credit to a non-military firm declines **26.9%** more than domestic credit in conflict
- Foreign credit to a military firm increases **23.4%** more than domestic credit in conflict

Robustness #1: Military sector classification

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

Other robustness tests

- Regression of loan shares ✓
- IHS-transformed dependent variable ✓
- Different AI dual-use thresholds ✓
- Clustering of standard errors ✓
- Conflict definition: discrete (✓) and continuous (✓)
- Loan share imputation ✓
- Excluding individual source countries ✓
- Excluding individual (small) lenders ✓

Credit supply versus demand

Dependent variable	$Loan_{bfsct}$					
	Baseline	Demand	Supply	Baseline	Demand	Supply
	(1)	(2)	(3)	(4)	(5)	(6)
Foreign × Conflict	-0.313***	-0.248	-0.275**	-0.469*	-0.299	-0.397*
	(0.116)	(0.155)	(0.112)	(0.251)	(0.326)	(0.205)
Foreign × Conflict × Military	0.523***	0.595***	0.099	0.555**	0.659**	0.047
	(0.105)	(0.105)	(0.133)	(0.235)	(0.259)	(0.364)
Bank FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓	✓	✓
Bank × Year FE		✓			✓	
Host Country × Military × Year FE			✓			✓
Bank × Firm FE				✓	✓	✓
N obs	1,308,048	1,273,395	1,307,976	690,405	664,711	690,213
N of banks	14,021	10,761	14,021	6,721	2,820	6,719
R^2 (adj.)	0.867	0.872	0.868	0.894	0.898	0.896

Firm-level data: Supportive evidence

Mechanisms

Mechanism #1: Geopolitical (mis)alignment

- Do global banks align lending practices with their home country's geopolitical interests, particularly in military-related financing?
  Kempf et al. 2023

- Classify countries according to:
  - Formal bloc memberships (NATO, BRICS, G7)
  - West vs. East geopolitical alignment based on voting patterns in the United Nations General Assembly
    Bailey, Strezhnev, and Voeten 2017

1/2 Geopolitical origin

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

2/2 Geopolitical (mis)alignment: dyadic analysis

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

Mechanism #2: Bank specialization

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

Extensions

Spillovers to neighboring countries during conflicts?

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

Post-conflict dynamics

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

Geographical distance

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

Private banks, state banks, and non-banks

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

Real effects on firms

- Pre-conflict exposure to cross-border lending shapes firm outcomes during conflict
  - Identification: IV-2SLS using pre-conflict foreign lending share as instrument for debt during conflict

- Divergent outcomes across firm types:
  - **Military firms** with greater pre-conflict exposure **expand** debt, assets, revenue, and employment
  - **Civilian firms** with greater pre-conflict exposure **contract** along the same dimensions

- Cross-border credit reallocation has real consequences for the structure of conflict economies

Conclusions

- During conflicts, global banks retrench overall but redirect credit toward military-related firms
- The effect is sharpest for geopolitically misaligned banks
- Private capital flows can reinforce or contradict official foreign policy
- As defense spending rises amid geopolitical fragmentation, these private channels deserve more scrutiny...

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Back-up slides

Absolute bank specialization

Back

- Country- and sector- bank lending shares:

$$\textit{Country Share}_{bct} = \frac{\sum_{f=1}^{F_{bct}} \textit{Loan}_{bct}}{\sum_{c=1}^{C_{bt}} \sum_{f=1}^{F_{bct}} \textit{Loan}_{bct}}, \qquad \textit{Sector Share}_{bst} = \frac{\sum_{f=1}^{F_{bst}} \textit{Loan}_{bst}}{\sum_{s=1}^{S_{bt}} \sum_{f=1}^{F_{bst}} \textit{Loan}_{bst}} \tag{3}$$

- Absolute specialization measures (averaged in time):

$$AS_{bc} = \begin{cases} 1, & \text{if } \textit{Country Share}_{bc} \geq \alpha_c \\ 0, & \text{if else} \end{cases} \qquad AS_{bs} = \begin{cases} 1, & \text{if } \textit{Sector Share}_{bs} \geq \alpha_s \\ 0, & \text{if else} \end{cases} \tag{4}$$

α_c and α_s are set at the corresponding 75^{th} percentile

Relative bank specialization
Paravisini, Rappoport, and Schnabl 2023

Back

Specialization:	Dependent variable: $Loan_{bft}$					
	Relative measure					
	In country ($RS_{bc} = 1$)		*P*-value *diff=0*	In sector ($RS_{bs} = 1$)		*P*-value: *diff=0*
	Yes	No		Yes	No	
	(1)	(2)		(3)	(4)	
Foreign × Conflict	-0.356***	-0.151	*0.323*	-0.253	-0.323**	*0.733*
	(0.123)	(0.167)		(0.175)	(0.108)	
Foreign × Conflict × Military	0.473***	0.566***	*0.651*	0.426**	0.645***	*0.329*
	(0.138)	(0.151)		(0.195)	(0.111)	
Bank FE	✓	✓		✓	✓	
Firm FE	✓	✓		✓	✓	
Home Country × Year FE	✓	✓		✓	✓	
Host Country × Year FE	✓	✓		✓	✓	
Conflict × Military FE	✓	✓		✓	✓	
Foreign × Military FE	✓	✓		✓	✓	
Military × Year FE	✓	✓		✓	✓	
Foreign × Year FE	✓	✓		✓	✓	
N obs	233,601	1,050,969		276,084	1,009,312	
N banks	2,100	11,781		2,788	11,124	
R^2 (adj.)	0.856	0.864		0.874	0.862	

Relative bank specialization
Blickle, Parlatore, and Saunders 2024

Back

Specialization:	Dependent variable: $Loan_{bft}$					
	Relative measure					
	In country ($RS_{bc} = 1$)		*P*-value *diff=0*	In sector ($RS_{bs} = 1$)		*P*-value: *diff=0*
	Yes	No		Yes	No	
	(1)	(2)		(3)	(4)	
Foreign × Conflict	-0.376***	-0.395**	*0.933*	-0.279	-0.293***	*0.950*
	(0.136)	(0.183)		(0.196)	(0.108)	
Foreign × Conflict × Military	0.431***	0.641***	*0.328*	0.615***	0.533***	*0.717*
	(0.154)	(0.151)		(0.185)	(0.131)	
Bank FE	✓	✓		✓	✓	
Firm FE	✓	✓		✓	✓	
Home Country × Year FE	✓	✓		✓	✓	
Host Country × Year FE	✓	✓		✓	✓	
Conflict × Military FE	✓	✓		✓	✓	
Foreign × Military FE	✓	✓		✓	✓	
Military × Year FE	✓	✓		✓	✓	
Foreign × Year FE	✓	✓		✓	✓	
N obs	234,349	1,051,771		267,295	1,017,829	
N banks	2,191	11,695		2,792	11,120	
R^2 (adj.)	0.854	0.865		0.868	0.865	

Examples of violent conflicts

Back

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

Country	Conflict Years	Conflict ID	Conflict Description
Algeria	1998, 1999	386	Since the early 1990s, Algeria has experienced an armed conflict over governmental power, primarily involving various Islamic groups seeking to establish an Islamic state by force. The Algerian Civil War (1992–2002) was marked by intense violence, particularly after the government's decision to cancel the 1991 elections, which an Islamist party was poised to win. The violence peaked in 1993 with widespread massacres and brutality. By 2002, some groups began to disarm and hostilities declined.
Colombia	1994, 1996, 1999, 2000, 2001, 2002, 2003, 2004, 2005	289	Colombia's conflict with the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN) spanned decades and centers on issues of land reform, inequality, and government control. The FARC, a Marxist guerrilla group, waged a violent insurgency beginning in the 1960s, leading to widespread violence, drug trafficking, and displacement. A landmark peace agreement in 2016 led to FARC's demobilization and transformation into a political party. The ELN, Colombia's last active guerrilla group, continues armed resistance despite periodic peace talks, focusing on ideological goals of social justice and economic reform.

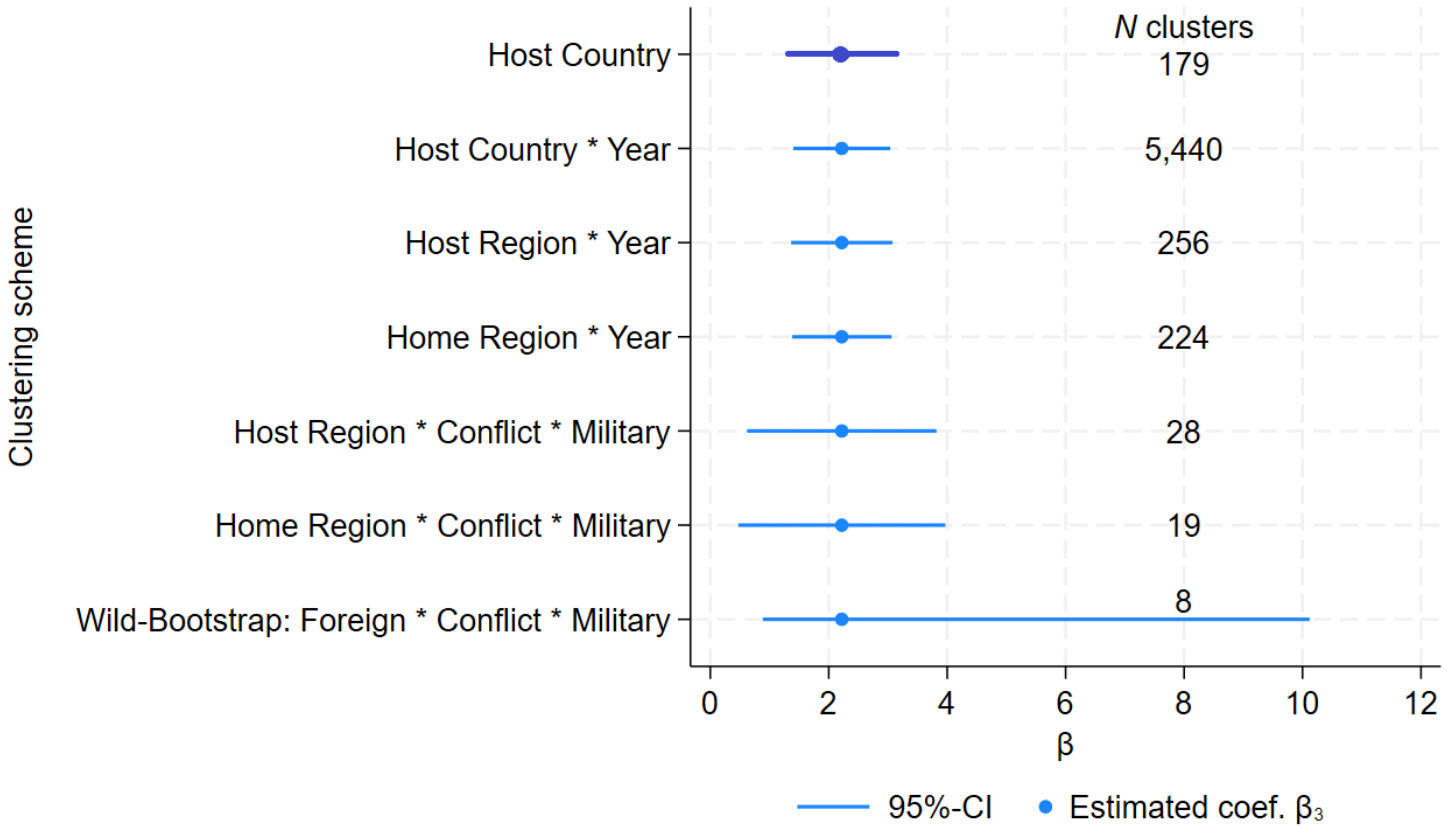
Tobit estimator

Back

	Dependent variable: $Loan_{gsct}$		
	(1)	(2)	(3)
Foreign	7.708***	8.739***	6.553***
	(0.195)	(0.235)	(1.255)
Foreign × Conflict	-4.097***	-4.720***	-4.344***
	(0.688)	(0.725)	(0.763)
Foreign × Military		-3.093***	-3.096***
		(0.294)	(0.292)
Foreign × Conflict × Military		3.023**	2.735**
		(1.266)	(1.278)
Conflict	✓	✓	✓
Host-country FE	✓	✓	✓
Foreign Region FE	✓	✓	✓
Year FE	✓	✓	✓
Conflict × Military FE			✓
Foreign × Military FE			✓
Military × Year FE			✓
Foreign × Year FE			✓
N obs	22,912	22,912	22,912
N of countries	179	179	179
R^2 (pseudo)	0.199	0.227	0.229

Clustering of standard errors

Back



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

Conflict definition: discrete thresholds

Back

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

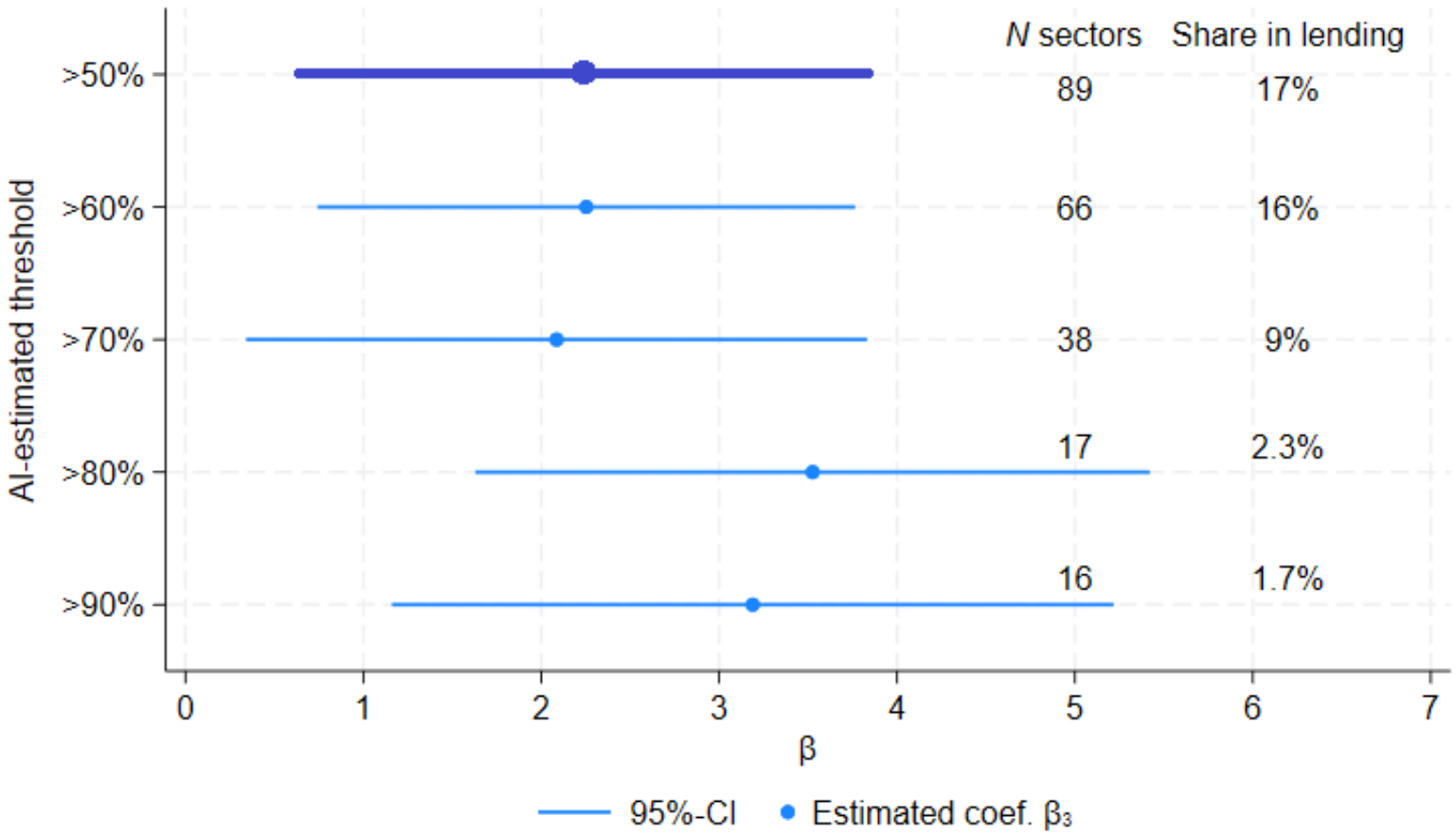
Conflict definition: continuous thresholds

Back

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

Different AI dual-use thresholds

Back



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

Loan share imputation

Back

Dependent variable	$Loan_{bft}$		
	(1)	(2)	(3)
Foreign × Conflict	-0.310***	-0.652*	-0.091
	(0.115)	(0.373)	(0.769)
Foreign × Conflict × Military	0.521***	1.270***	1.331***
	(0.105)	(0.397)	(0.502)
Bank FE	✓	✓	✓
Firm FE	✓	✓	✓
Home Country × Year FE	✓	✓	✓
Host Country × Year FE	✓	✓	✓
Conflict × Military FE	✓	✓	✓
Foreign × Military FE	✓	✓	✓
Military × Year FE	✓	✓	✓
Foreign × Year FE	✓	✓	✓
N obs	1,308,048	1,308,048	1,307,507
N of banks	14,021	14,021	14,016
R^2 (adj.)	0.868	0.539	0.428

Note: The table shows the results after imputing the missing loan shares in different ways. Column (1) shows our baseline specification. In column (2), following De Haas and Van Horen 2013, lead banks and non-lead banks are each allocated 50% of the loan share and then shares are split equally across banks with the same role in the syndicate. In column (3), we assign the entire loan volume to the lead bank when there is only one lead bank. In case of multiple lead banks, the loan amount is divided equally among them.

Excluding individual source countries

Back

Dependent variable	$Loan_{bft}$			
Excl. banks from	US	Japan	DE & FR	China
	(1)	(2)	(3)	(4)
Foreign × Conflict	-0.316***	-0.301***	-0.301**	-0.320***
	(0.117)	(0.116)	(0.118)	(0.116)
Foreign × Conflict × Military	0.551***	0.529***	0.489***	0.540***
	(0.112)	(0.107)	(0.111)	(0.108)
Bank FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Home Country × Year FE	✓	✓	✓	✓
Host Country × Year FE	✓	✓	✓	✓
Conflict × Military FE	✓	✓	✓	✓
Foreign × Military FE	✓	✓	✓	✓
Military × Year FE	✓	✓	✓	✓
Foreign × Year FE	✓	✓	✓	✓
N obs	872,880	1,104,600	1,143,206	1,271,769
N of banks	9,399	12,681	12,799	13,106
R^2 (adj.)	0.890	0.765	0.875	0.869

Excluding individual (small) lenders

Back

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

Note: The sample is drastically reduced to only the 575 largest global syndicated lenders.