U.S. Trade Policy and Euro Area Bank Lending*

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Abstract

We study how the 2025 shift in U.S. trade policy reached euro area firms through their banks. Using the euro area credit register, we measure banks' exposure through their borrowers' dependence on U.S. trade and compare lending by more and less exposed banks to the same firm. After the April 2025 tariff announcement, a one-standard-deviation more exposed bank reduced credit supply by 1.9 percent relative to the firm's other lenders. The contraction appeared immediately and persisted through the end of 2025. It was stronger at more exposed and at smaller banks, reached borrowers irrespective of their own sector's exposure, and fell most heavily on the smallest firms. Banks' portfolios thus transmit a foreign trade policy shock to domestic firms well beyond those directly exposed.

JEL classification: E44, F42, G21

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1. Introduction

On April 2, 2025—"Liberation Day"—the United States announced a sweeping increase in import tariffs. Within weeks, the U.S. effective tariff rate rose to a level not seen in a century and trade policy uncertainty reached an unprecedented peak (International Monetary Fund, 2025). Could this shock tighten credit for firms with little direct exposure to U.S. trade through the balance sheets of their lenders? This paper shows that it can. Euro area banks whose borrower portfolios were more exposed to U.S. trade reduced committed credit after the announcement relative to less-exposed banks lending to the same firm. The contraction also reached borrowers with little direct exposure of their own.[1]

The episode combined a large increase in tariffs with an unprecedented rise in trade policy uncertainty and the prospect of a reorganization of supply chains. We do not separate these channels. Our measure of exposure captures how dependent a bank's borrowers are on U.S. trade, not the tariff rate each of them faces, so the estimates describe the lending response to the shift in U.S. trade policy as a whole; we refer to it as the trade policy shock. The timing is nonetheless informative. Trade policy uncertainty had been rising since late 2024, but lending by more- and less-exposed banks diverged only when tariffs were announced. The event study therefore ties the differential response to the April policy shift rather than to a pre-existing divergence in lending.

Banks' own reports point in the same direction. In the January 2026 euro area bank lending survey, almost half of the participating banks considered their exposure to trade policy important, and a net 11 percent attributed tighter credit standards to changes in trade policy and the associated uncertainty (European Central Bank, 2026). The same banks also reported weaker loan demand. The survey documents the channel in banks' own accounts, but also shows why aggregate lending cannot establish it: tighter supply and weaker demand move lending in the same direction. Separating the two requires observing how different lenders treat the same borrower.

To do so, we combine three sources of granular data. From Eurostat's FIGARO-based Macroeconomic Globalisation Indicators, we measure the domestic value added in each country–sector pair that is linked, directly or through global input–output linkages, to trade with the United States. From AnaCredit, the euro area credit register, we recover banks' lending portfolios in the first half of 2024 and observe monthly committed credit within individual bank–firm relationships from July 2024 through December 2025. ECB balance-sheet statistics provide predetermined bank characteristics. The baseline sample

[1] The United States absorbed 21 percent of goods exported from the EU in 2025 (Eurostat, 2025), while bank loans remain euro-area firms' main source of external finance (Adalid et al., 2020).

covers 471 banks (Significant Institutions under the Single Supervisory Mechanism, and their subsidiaries), 2.7 million firms, and 3.4 million lending relationships in 20 euro area countries. A bank's exposure is the average U.S. trade exposure of its borrowers' country–sector U.S. trade exposure, weighted by their share in its portfolio before the shock. Both ingredients are fixed before the estimation window, so exposure cannot respond to the shock itself.

Our empirical strategy compares the lending of more- and less-exposed banks to the same firm in the same month (Khwaja and Mian, 2008). Firm–time fixed effects absorb changes in a firm's total credit demand, including those caused by tariffs, uncertainty, or supply-chain disruption; bank–firm fixed effects absorb persistent differences across lending relationships. Because exposed banks differ from other banks in size, business model, and sectoral specialization, we further allow lending after the shock to vary with predetermined bank characteristics and with the bank's specialization in the borrower's sector (Paravisini et al., 2023). The identifying assumption is that, conditional on these controls, banks did not sort into sectors on characteristics that also drive their post-shock lending (Borusyak et al., 2022). Pre-shock lending paths and the event-study estimates support this notion.

We find a clear differential contraction in credit supply. After April 2025, a bank with one-standard-deviation higher exposure to U.S. trade reduced committed credit to a given firm by 1.9 percent relative to the firm's other lenders. The estimate is significant at the 1 percent level and stable across control sets. Because the outcome is committed rather than drawn credit, it captures a reduction in the amount a bank makes available even if firms respond to the shock by drawing on existing credit lines. The response is about a quarter of the contraction that Federico et al. (2025a) estimate for Italian banks whose borrowers faced import competition after China's entry into the WTO.

The timing reinforces the interpretation that the shift in U.S. trade policy led banks with greater exposure to U.S. trade to cut credit supply. Lending by more- and less-exposed banks follows similar dynamics before April 2025: the event-study coefficients display neither a differential trend nor an anticipatory decline, although trade policy uncertainty had been rising for months (Figure D.1). They turn negative in the month of the announcement and remain close to 2 percent through December 2025. The baseline effect is therefore not a short-lived adjustment but a persistent divergence in the level of credit supplied by banks with different portfolio exposure.

We then ask which banks contract credit supply and where within their portfolios the cuts fall. On the bank side, the response steepens as exposure rises, is weaker at larger banks, and is stronger where the bank is relatively specialized in the borrower's sector.

On the borrower side, the contraction propagates across sectors: for firms in sectors below the median of U.S. trade exposure, a one-standard-deviation increase in bank exposure reduces committed credit by 1.8 percent, against 2.0 percent for firms in sectors above it, a difference that is neither economically nor statistically significant. Firm size matters more. The cut falls from 2.8 percent for micro firms to 0.9 percent for large firms. A firm can thus face tighter credit not because its own activity is tied to U.S. trade, but because it borrows from a bank whose other borrowers are. Portfolio exposure determines which lenders respond; borrower and relationship characteristics determine where their cuts fall.

We use a simple portfolio model to interpret these two margins. A bank enters the shock with existing commitments and some spare intermediation capacity. Its predetermined portfolio exposure determines the pressure on that shared capacity. If spare capacity absorbs the pressure, commitments need not change. Once the constraint binds, a common shadow cost reduces commitments across the bank. This threshold produces a nonlinear exposure response; greater spare capacity shifts it outward, consistent with the weaker response at larger banks. Within the portfolio, the capacity released relative to the adjustment cost of cutting a relationship determines where the contraction falls. This allocation margin allows the shock to reach borrowers with little direct U.S. exposure and provides a way to interpret the stronger cuts to micro firms and specialized relationships.

Existing work shows that trade shocks and trade uncertainty can contract lending at exposed banks (Federico et al., 2025a; Correa et al., 2026). Our contribution lies in locating that response within ongoing bank–firm relationships during the 2025 policy shift. Monthly commitments and same-firm–same-month comparisons separate which banks come under pressure from where within their portfolios the response falls. The results show that the lending incidence of trade policy extends beyond firms' own trade links and falls most heavily on the smallest firms. This matters for who bears the cost of trade policy and for whether diversified lenders dampen or spread it.

Related literature. A broad literature studies how finance shapes the transmission of trade shocks. Trade-policy uncertainty delays investment and trade, while tariffs change costs, demand, and cash flows (Handley and Limao, 2015; Caldara et al., 2020; Amiti et al., 2019; Fajgelbaum et al., 2020; Benguria and Saffie, 2024). Bank credit, in turn, shapes firms' exports and their adjustment across foreign markets (Amiti and Weinstein, 2011; Paravisini et al., 2015, 2023). That work mainly treats finance as an input into firms' own trade decisions. Our mechanism runs in the other direction: a real shock enters through the borrower portfolio and changes the bank's supply of credit, including to firms that are not themselves highly exposed.

Banks can either absorb real-sector shocks or transmit them across borrowers. Relationship lending and sectoral expertise may support affected firms (Federico et al., 2025b; Alfaro et al., 2025; Giannetti and Saidi, 2019); losses or higher perceived risk may instead reduce credit elsewhere in the portfolio (Federico et al., 2025a; Cao et al., 2023; Mayordomo and Rachedi, 2022; Correa et al., 2026; Da, 2026). Banks may thus protect affected or core borrowers while reallocating credit away from others (Calani et al., 2025; Deng and Pu, 2025). This tension also makes the role of specialization ambiguous: it may reflect information and support for core clients, but also endogenous matching between firms and banks (Müller, 2020; Izadi and Saadi, 2023; De Jonghe et al., 2020; Iyer et al., 2022; Paravisini et al., 2023; Berthou et al., 2024). We therefore distinguish a firm's own trade exposure from its lender's portfolio exposure and account for predetermined bank–sector specialization.

Closest in spirit are studies that trace shocks across borrowers sharing a lender (Khwaja and Mian, 2008; Giannetti and Saidi, 2019; De Jonghe et al., 2020; Iyer et al., 2022). Our same-firm comparison isolates this supply-side propagation: the more-exposed bank contracts more while both banks serve the same borrower. Sector and size splits show where the contraction falls.

Credit responses also depend on contract type and access to other finance. During the 2025 episode, commitments and credit-line utilization moved differently at exposed U.S. banks (Morgan et al., 2026), while bank-lending channels more generally vary across cash-flow loans, asset-based lending, trade finance, and leasing (Ivashina et al., 2022). Firms may also replace bank credit through internal capital markets or cross-border firm-to-firm finance (Imbierowicz et al., 2025; Correa et al., 2025). These distinctions motivate our focus on committed credit.

A small recent literature studies the 2025 episode. Market studies find larger valuation losses at banks with greater trade-related vulnerabilities (Uysal et al., 2025; Modugno et al., 2026), Soyres et al. (2025) document substantial trade frontloading, and Avril et al. (2026) find that trade-policy uncertainty reduces euro area bank lending, especially at exposed and less-capitalized banks. In a recent ECB blog, Allayioti et al. (2026) find that bank credit supply, measured as the bank component of loan growth in an Amiti–Weinstein decomposition, contracts more at exposed banks after April 2025. We trace the response within bank–firm relationships and show that it is a persistent shift in the level of credit. We also characterize its heterogeneity on both sides of the relationship: on the bank side, the contraction steepens with exposure, is weaker at larger banks, and is stronger where the bank is specialized in the borrower's sector; on the firm side, it reaches borrowers in sectors with little direct U.S. exposure and falls most heavily on micro firms.

Outline. Section 2 describes the data and exposure measure. Section 3 presents the empirical strategy and results. Section 4 offers a simple portfolio interpretation of the findings. Section 5 concludes.

2. Data and Measurement

To measure banks' exposure to the April 2025 U.S. trade policy shock and trace their subsequent lending response, we combine the Eurosystem's harmonized credit register (AnaCredit), the ECB's Individual Balance Sheet Items (IBSI), and Eurostat's FIGARO-based trade indicators. FIGARO supplies country–sector trade linkages; AnaCredit maps these linkages into banks' pre-shock portfolios and tracks subsequent bank–firm lending. IBSI supplies pre-shock bank balance-sheet characteristics. Table 1 summarizes the unit, period, and use of each input.

We first describe AnaCredit, define the sample, and introduce the lending and bank balance-sheet measures. We then construct bank exposure from FIGARO trade linkages and pre-shock loan portfolios and describe its cross-sectional variation.

Table 1: Data Sources, Periods, and Uses

Data source	Unit	Period used	Use in analysis
Eurostat FIGARO	Country–NACE sector	2023	Country–sector U.S. trade exposure
AnaCredit	Bank–firm	January–June 2024	Portfolio weights and sectoral specialization
IBSI	Bank	January–June 2024	Pre-shock balance-sheet characteristics
AnaCredit	Bank–firm	July 2024–December 2025	Lending outcomes and other credit terms

Notes: FIGARO refers to Eurostat's FIGARO-based Macroeconomic Globalisation Indicators; IBSI refers to the ECB's Individual Balance Sheet Items statistics. January–June 2024 inputs predate both the estimation window and the April 2025 trade policy shock.

2.1. Credit register and bank balance sheet data

Credit register. AnaCredit records monthly credit exposures above 25,000€ to euro-area legal entities at the instrument level. Lender and borrower identifiers allow us to follow individual bank–firm relationships over time.[2]

Baseline sample. We construct the baseline sample in three steps. First, we retain lending by euro area deposit-taking institutions to private non-financial corporations and aggregate instrument records to the bank–firm–month level.[3] Second, we restrict lenders to those that were (part of) a Significant Institution under the Single Supervisory Mechanism (SSM) at the start of our sample (January 2024) and located in the 20 countries that belonged to the euro area throughout the sample period. This common supervisory perimeter improves cross-country comparability because reporting is more complete and consistent.

The resulting sample contains 471 banks, 2.66 million firms, and 3.41 million bank–firm relationships. It accounts for about 74 percent of committed credit in the deposit-taking-institution sample before the SSM restriction. Table B.3 in the appendix reports summary statistics for that unrestricted comparison sample.

Lending outcomes. Our main outcome is the committed amount of non-revolving credit lines and other loans. A commitment is the amount a bank has agreed to provide, whether or not the firm has drawn it. Together, these instruments account for 73 percent of committed credit to euro-area non-financial corporations (NFCs) and primarily finance longer-term funding needs rather than short-term liquidity management.

A drawdown affects committed and outstanding credit differently: the outstanding amount rises, but the commitment need not. Our outcome therefore helps distinguish changes in banks' willingness to lend from firms' use of previously granted credit. This distinction is especially useful here: credit-line utilization rose markedly after the April 2025 tariff announcements at U.S. banks more exposed to supply-chain risk (Morgan et al., 2026).

[2] Appendix B.3 provides further details on the AnaCredit data and sample construction.

[3] The lenders are Monetary Financial Institutions classified as "deposit-taking corporations except central banks" (sector S.122 in the European System of Accounts 2010). This class comprises institutions that accept deposits or close substitutes and extend credit on their own account; it excludes central banks and money market funds.

Table 2: Baseline Sample

Variable	Mean	SD	P25	Median	P75	N
Panel A: Bank–firm relationships						
Outstanding amount (€)	681,275	10,948,437	34,537	83,830	249,548	3,409,825
Committed amount (€)	749,540	14,285,660	35,360	86,582	259,598	3,409,825
Interest rate (annual %)	3.62	2.36	1.90	3.63	4.82	3,409,825
Residual maturity (years)	5.14	4.76	1.86	3.61	6.57	3,387,546
Probability of default (%)	5.66	15.68	0.42	1.10	3.26	2,538,213
Panel B: Firms						
Firm age (years)	15.71	15.38	5.67	11.00	21.67	2,658,995
Employees	81.74	8,088.75	1.00	2.00	8.00	2,211,255
Number of lenders	1.20	0.63	1.00	1.00	1.00	2,658,995
Number of lenders (conditional on $N > 1$)	2.40	0.94	2.00	2.00	2.39	466,755

Notes: The table reports one observation per bank–firm relationship or firm in the baseline SSM-bank sample. Relationship characteristics are averaged over July 2024–December 2025. Interest rates and residual maturity are weighted by outstanding amounts. Number of lenders conditional on $N > 1$ refers to firms with multiple lenders. Counts vary with data availability. Monetary amounts are in euros.

Additional measures. Beyond commitments, AnaCredit reports outstanding amounts, interest rates, and residual maturity. As outlined above, outstanding amounts capture credit actually drawn, while interest rates and residual maturity describe the price and maturity of credit within each relationship. Borrower default risk, age, and employment allow us to characterize risk and firm demographics.

Bank balance sheets. We obtain bank-level balance sheets separately from the ECB's IBSI statistics. From IBSI, we retain monthly total assets and the balance-sheet shares of loans to and deposits from non-financial corporations, household loans and deposits, and euro area government securities. We average each characteristic over January–June 2024, before both the estimation window and the trade policy shock.

Relationships and borrowers. Table 2 summarizes the baseline sample. Panel A reports credit, pricing, maturity, and default risk within bank–firm relationships; Panel B reports firm age, employment, and lender counts.

The distribution of credit is strongly right-skewed: the median relationship has a commitment of 86,582€, compared with a mean of 749,540€. The average interest rate is 3.62

percent, and residual maturity averages 5.1 years. The median firm is about 11 years old, has two employees, and borrows from one bank.

Lender structure and relationship dynamics. Most firms borrow from a single bank. Multi-bank firms, however, are economically important: the 480,165 such firms account for about 64 percent of committed credit and provide the within-firm, across-bank variation used in the baseline. Among them, 35 percent borrow from banks on both sides of the median exposure distribution; only 2 percent borrow from banks in both outer quartiles.

Of all relationships, 57 percent are observed throughout the sample, while 18 percent exit and 18 percent enter. The baseline estimates are therefore driven by changes within relationships while they remain observed.

Firm size. We classify firms as micro, small, medium, or large using the European Commission definition, which combines employment with balance-sheet size or annual turnover (Kosekova et al., 2023). Size is available for 2.46 million firms, about 93 percent of the baseline sample. Table 3 shows that borrowing and lender access rise sharply with firm size. Average committed credit increases from 0.36 million euros for micro firms to 10.5 million euros for large firms, while the average number of lenders rises from 1.29 to 4.36. Large firms are also older and have lower measured default risk. These differences make size a useful dimension for the heterogeneity analysis. Table B.4 in the appendix reports the joint distribution of firm age and size.

2.2. Bank exposure to U.S. trade

We now use each bank's pre-shock borrower portfolio to construct its treatment: exposure to U.S. trade. FIGARO supplies country–sector exposure, while AnaCredit supplies the portfolio weights. Following Federico et al. (2025a), the construction proceeds in two steps: we first measure exposure for each country–sector pair and then aggregate it across the bank's portfolio.

Country–sector exposure. Eurostat constructs its trading-partner exposure indicator from FIGARO's inter-country input–output tables. It traces domestic value added that reaches the United States directly or through third countries, enters U.S. production, or passes through U.S. production before being re-exported. Compared with gross bilateral exports, the indicator makes two adjustments: it removes foreign inputs embedded in direct shipments and adds domestic value added carried through other countries or U.S.

Table 3: Firm Characteristics by Size

	Micro	Small	Medium	Large
Panel A: Credit characteristics				
Outstanding amount (EUR)	335,598	579,456	2,025,012	9,311,450
Committed amount (EUR)	357,912	611,158	2,184,571	10,454,883
Interest rate (annual %)	3.57	3.64	3.50	3.70
Residual maturity (years)	5.96	3.61	3.38	3.72
Probability of default (%)	5.82	5.23	4.19	2.97
Panel B: Firm characteristics				
Firm age (years)	15.29	22.65	30.23	33.02
Employees	2.32	18.70	79.14	5,114.09
Number of lenders	1.29	2.03	3.22	4.36
Number of lenders (cond. $N > 1$)	2.36	2.89	3.97	5.27

Notes: The table reports means by European Commission firm-size class in the baseline SSM-bank sample. Panel A describes bank–firm relationships; Panel B describes firms. Monetary amounts are in euros.

production. Together, these adjustments capture how strongly production in a country–sector is tied to U.S. trade, rather than only the value of its direct shipments to the United States. To make exposure comparable across country–sector pairs, we scale the indicator by domestic gross value added, also from Eurostat:

$$\text{Country–sector exposure}_{c,s}^{\text{US}} = 100 \times \frac{\text{Trading-partner exposure}_{c,s}^{\text{US},2023}}{\text{Gross value added}_{c,s}^{2023}}, \tag{1}$$

where c denotes country and s the two-digit NACE sector.[4] We take data from 2023, the most recent year for which data was available. We express the resulting ratio as a percentage of country–sector gross value added.

Bank exposure. In the second step, we map country–sector exposures into bank portfolios. We assign each borrower the exposure of its country–sector pair and define bank

[4]For further detail and graphical illustrations of trading-partner exposure, domestic value added in exports, and domestic value added in foreign final use, see Appendix B.1. Appendix B.2 lists the included two-digit NACE sectors and documents their cross-country variation.

exposure as the resulting credit-weighted average:

$$\text{Bank exposure}_b = \sum_{c,s} \omega_{b,c,s}^{2024H1} \times \text{Country–sector exposure}_{c,s}^{\text{US}}, \tag{2}$$

$$\omega_{b,c,s}^{2024H1} = \frac{\text{Average committed amount}_{b,c,s}^{2024H1}}{\text{Average total committed amount}_b^{2024H1}}. \tag{3}$$

Because the weights sum to one, bank exposure remains on the country–sector percentage scale; it is not a portfolio share. The weights draw on all credit instruments, not only those in the lending outcome, so bank exposure summarizes the entire credit portfolio. Both components are predetermined: country–sector exposure refers to 2023, and portfolio weights are averaged over January–June 2024. The measure thus captures a bank's ex ante exposure to U.S. trade and cannot respond mechanically to economic conditions surrounding the 2025

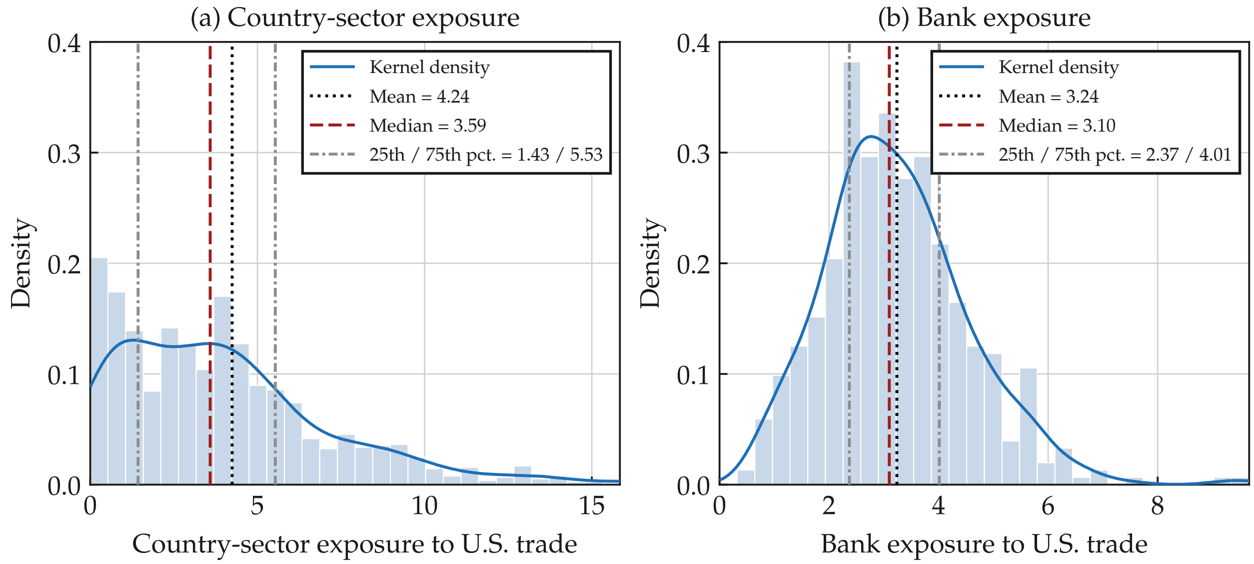
Exposure variation. Figure 1 shows the variation at both stages. At the country–sector level, exposure is widely dispersed and strongly right-skewed: its median is 3.59 percent of gross value added, its interquartile range is 1.43–5.53 percent, and its upper tail extends to 37 percent (left panel). Water transport, pharmaceuticals, and basic metals have the highest average exposure; human health and social work activities, education, and other service activities have the lowest. These sector rankings also mask variation across countries within the same sector (Figure B.4).

Portfolio aggregation narrows this dispersion without eliminating it. At the bank level, the credit-weighted measure remains on the same percentage scale. Its distribution is unimodal and moderately right-skewed (right panel), with a mean of 3.24, a median of 3.10, and an interquartile range of 2.37–4.01. The design therefore uses continuous exposure variation across a broad set of banks, not a comparison of a few specialized lenders.

2.3. Exposure and predetermined bank characteristics

Portfolio composition. Panel A of Table 4 shows that bank exposure captures a portfolio tilt, not complete specialization. Banks above the bank-exposure median allocate 51 percent of pre-shock credit to country–sector pairs above the country–sector exposure median, compared with 20 percent among banks below the bank-exposure median. Thus, the two groups differ substantially in their exposure to U.S. trade, even though both lend to country–sectors on either side of the exposure distribution. Panel A also shows that more-exposed banks have greater non-U.S. trade exposure, indicating that U.S. expo-

Figure 1: Distribution of Exposure to U.S. Trade



Notes: The left panel shows country–sector exposure, expressed as a percentage of country–sector gross value added, as defined in Equation (1); the displayed range is truncated at the 98th percentile, while the maximum is 37 percent. The right panel shows the corresponding credit-weighted bank measure defined in Equation (2) for the baseline SSM sample.

sure partly captures a broader international orientation. We therefore control for non-U.S. trade exposure in a sensitivity check.

Predetermined bank characteristics. Panel B of Table 4 shows that more-exposed banks are larger, have smaller household loan and deposit shares, hold more euro area government securities, and are more specialized in their borrowers' sectors. Their non-financial corporate loan and deposit shares are similar. We also include a measure of portfolio-weighted bank specialization following Blickle et al. (2023) to capture how active banks are in different sectors (see Appendix B.4.1 for construction details). While on average across all banks there is some degree of specialization, this tends to increase with the level of bank exposure to U.S. trade. Together, the six balance-sheet characteristics and specialization explain 22 percent of the cross-sectional variation in exposure. These descriptive differences do not test parallel trends, but they show why bank–firm fixed effects alone are insufficient: banks with different pre-shock business models may follow different lending paths after April 2025. Our baseline therefore interacts each predetermined bank characteristic and bank–sector specialization with the post-shock indicator.

Table 4: Bank Exposure and Pre-Shock Characteristics

Variable	Below median	Above median	Norm. diff.	Slope (SE)
Panel A: Trade exposure and portfolio composition				
Credit share in high-U.S.-exposure country–sectors (%)	20.04	50.47	1.75	–
Non-U.S. trade exposure	12.31	20.23	1.46	–
Panel B: Predetermined bank characteristics				
Log total assets	8.70	9.37	0.35	0.373 (0.088)
NFC loan share	0.219	0.240	0.12	0.001 (0.008)
HH loan share	0.312	0.200	-0.58	-0.066 (0.009)
NFC deposit share	0.122	0.136	0.13	0.007 (0.005)
HH deposit share	0.350	0.235	-0.49	-0.063 (0.011)
EA government securities share	0.068	0.096	0.24	0.008 (0.005)
Portfolio-weighted specialization	1.29	1.50	0.31	0.154 (0.030)

Notes: The table splits the 471 SSM banks at the median of bank-level U.S. trade exposure. Columns report group means, normalized differences, and, for Panel B, the slope from a separate OLS regression on standardized U.S. exposure (standard error in parentheses). Normalized differences divide the above-minus-below difference in means by the root mean square of the two group standard deviations. Bank characteristics are January–June 2024 averages. The high-exposure share is the percentage of committed credit allocated to country–sector pairs above the median U.S. exposure. Non-U.S. trade exposure is constructed analogously from country–sector non-U.S. exposure. In a joint regression of standardized U.S. exposure on the seven Panel B characteristics, $F(7, 463) = 20.279$, $p < 0.001$, and adjusted $R^2 = 0.22$.

3. Empirical Strategy and Results

On April 2, 2025, the United States announced a broad increase in import tariffs, accompanied by a sharp rise in trade policy uncertainty. Our exposure measure captures how dependent a bank's pre-shock borrower portfolio was on U.S. trade, not the tariff rate each borrower faced. The estimates therefore capture banks' lending response to the policy shift as a whole; they do not separate higher tariffs from the uncertainty and adjustment that followed. We refer to this episode as the trade policy shock. This section sets out the specification and the assumptions behind it, estimates the average and the monthly response, and then examines heterogeneity, specialization, and other margins of adjustment.

3.1. Identification

Within-firm comparison. Our identification comes from firms that borrow from more than one bank. These firms let us compare committed lending by more- and less-exposed banks to the same firm in the same month, as in Khwaja and Mian (2008). The comparison is therefore across lenders facing the same borrower at the same point in time.[5]

We implement this comparison with the following static difference-in-differences specification:

$$\begin{aligned}\log L_{i,b,t} = {} & \beta\,(\text{Bank exposure}_b \times \text{Post}_t) + \rho'\left(X_b^{\text{pre}} \times \text{Post}_t\right) \\ & + \theta\left(Z_{b,s(i)} \times \text{Post}_t\right) + \alpha_{i,t} + \alpha_{i,b} + \varepsilon_{i,b,t},\end{aligned} \tag{4}$$

estimated at the bank–firm–month level for SSM banks.

The dependent variable, $\log L_{i,b,t}$, is the log committed loan amount from bank b to firm i in month t. Bank exposure$_b$ is the portfolio-weighted measure defined in Equation (2). It is predetermined: the portfolio weights are fixed over January–June 2024, before the estimation window, and the measure is standardized in the regressions. Post$_t$ equals one from April 2025 onward.

The vector X_b^{pre} contains predetermined bank characteristics, also averaged over January–June 2024: log total assets, the shares of loans to and deposits from non-financial corporations and households, and the share of euro area government securities. The variable $Z_{b,s(i)}$ measures bank b's specialization in firm i's sector; its construction is described in Appendix B.4.1. Because these variables are fixed before the estimation window, their levels are absorbed by the bank–firm fixed effects. We estimate only their interactions with the post-shock indicator.[6]

The coefficient of interest, β, measures the differential change in lending after April 2025 by more-exposed banks relative to less-exposed banks lending to the same firm. We multiply the coefficient by 100, so that it gives the approximate percentage change in lending associated with a one-standard-deviation increase in exposure.

The two sets of fixed effects serve distinct purposes. Firm–time fixed effects, $\alpha_{i,t}$, absorb changes in a firm's credit demand that are common across its lenders. Thus, β is identified from differences across the same firm's banks in the same month. Bank–firm fixed effects, $\alpha_{i,b}$, absorb persistent differences across lending relationships, including those

[5]Single-lender firms do not contribute to this comparison. Table 6 includes them using country–sector–firm-size–time fixed effects in the spirit of Degryse et al. (2019).

[6]The results are robust to including the control variables as one-month lagged values (See Table D.2).

arising from endogenous matching (see, e.g., Chodorow-Reich, 2014; Schwert, 2018).

Conditional parallel trends. The identifying assumption is conditional parallel trends. Absent the trade policy shock, more- and less-exposed banks lending to the same firm would have changed their commitments similarly. Firm–time and bank–firm fixed effects do not guarantee this condition. In particular, exposure may co-vary with banks' business models, while sectoral specialization may generate time-varying credit demand specific to a particular lender. We address these two concerns in turn.

First, bank exposure may reflect systematic portfolio sorting. Banks with different size, business models, or sectoral expertise may have entered the pre-shock period with different country–sector portfolios (Borusyak et al., 2022). Table 4 shows that more-exposed banks are larger, have lower household loan and deposit shares, hold more euro-area government securities, and are more specialized in their borrowers' sectors. Their NFC loan and deposit shares are similar. Together, the six balance-sheet characteristics and specialization explain 22 percent of the cross-sectional variation in exposure. Interacting these predetermined characteristics with the post-shock indicator allows banks with different pre-shock business models to follow different lending paths after April 2025. More-exposed banks also have greater non-U.S. trade exposure; we include its post-shock interaction as a sensitivity check.

Second, bank exposure may proxy for sectoral specialization. If exposed banks specialize in tradable sectors, the shock may change a firm's demand for credit from those banks relative to its demand from other lenders. Firm–time fixed effects do not absorb such lender-specific credit demand. Without an additional control, the within-firm comparison could therefore combine a credit-supply response with a change in how the firm allocates its borrowing across banks (Paravisini et al., 2023). The interaction $\theta\left(Z_{b,s(i)} \times \text{Post}_t\right)$ allows banks that are overweight in the borrower's sector to follow a different post-shock lending path. The monthly event study in Section 3.2 provides the main conditional evidence on parallel trends.

Finally, the baseline conditions on lending relationships that remain observed (Khwaja and Mian, 2008; Jiménez et al., 2020). The coefficient β therefore captures intensive-margin adjustments among continuing relationships. Standard errors are two-way clustered at the bank and sector level, reflecting treatment variation across banks and correlated lender behavior toward firms in the same sector (Abadie et al., 2023).

Table 5: Bank Exposure to U.S. Trade and Lending after April 2025

	(1)	(2)	(3)	(4)	(5)
US exposure (std.) × Post	-2.328***	-2.083**	-1.699***	-1.871***	-2.074**
	(0.793)	(0.836)	(0.626)	(0.702)	(0.856)
Non-US exposure (std.) × Post					0.208
					(0.494)
Bank controls × Post		Yes		Yes	Yes
Bank fixed effects	Yes	Yes			
Firm fixed effects	Yes	Yes			
Time/date fixed effects	Yes	Yes			
Bank-Firm fixed effects			Yes	Yes	Yes
Firm-Time fixed effects			Yes	Yes	Yes
Observations	17,754,847	17,754,847	17,754,847	17,754,847	17,754,847
Adjusted R^2	0.753	0.756	0.960	0.960	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Bank exposure to U.S. trade is standardized. Bank controls are the January–June 2024 characteristics listed in Section 3.1 and specialization is defined in Equation (B.1); both enter interacted with the post indicator, which equals one from April 2025 onward. Column (5) adds non-U.S. trade exposure interacted with the post indicator. Coefficients are multiplied by 100. Standard errors are clustered by bank and sector.

3.2. Average Bank Lending Response

Static difference-in-differences. Table 5 reports estimates of Equation (4). Columns (1) and (2) include bank, firm, and month fixed effects, which do not control for time-varying credit demand at the firm level; columns (3) to (5) use the bank–firm and firm–time fixed effects of Equation (4). Column (4), which adds the predetermined bank controls and specialization, is our baseline. Moving from separate to interacted fixed effects lowers the estimate from -2.3 to -1.7 (columns 1 and 3), indicating that part of the raw differential reflects the borrowers that exposed banks serve rather than the banks' own response. The estimate is rather stable when the bank controls are added (column 4) and when non-U.S. trade exposure is added (column 5); the coefficient on non-U.S. exposure itself is small and imprecise.

The baseline estimate implies that, after April 2025, a bank with one-standard-deviation higher exposure to U.S. trade (1.3 in the units of Equation (2)) reduced committed credit to a given firm by 1.9 percent relative to the firm's other lenders. The estimate is significant at the 1 percent level. Because the comparison is within firm and month, this differential is not driven by a decline in the firm's total credit demand. Because the outcome is committed rather than drawn credit, it reflects a reduction in the amount banks make available, even where firms respond to the shock by drawing on existing lines.

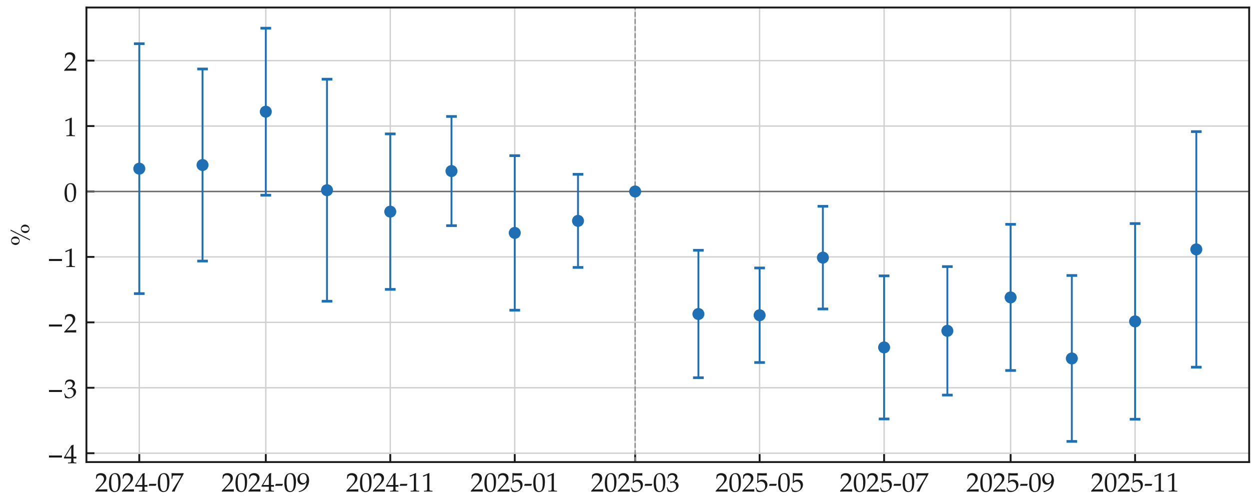


Figure 2: Dynamic Effect of Bank Exposure to U.S. Trade on Lending

Notes: The figure reports the coefficients on bank exposure interacted with event-time indicators, multiplied by 100; March 2025 is the omitted period and the vertical dashed line denotes April 2025. Whiskers show 95 percent confidence intervals. The specification includes bank–firm and firm–time fixed effects, predetermined bank controls and bank–sector specialization, each interacted with event-time indicators.

These results are robust to different forms of clustering (see Table D.1), taking one-period lagged values of the controls rather than pre-determined values and excluding Ireland from the estimation sample (see Table D.2).

Dynamic difference-in-differences. To trace the response over time, we replace the post indicator in Equation (4) with a full set of monthly event-time indicators, from nine months before to eight months after April 2025, with March 2025 as the omitted reference month. The bank controls and specialization measure are interacted with the same indicators; everything else is as in Equation (4). The coefficients on exposure for the months before April 2025 trace differential pre-trends, and those from April 2025 onward the dynamic response to the shock.

Figure 2 shows no differential movement in lending by more-exposed banks before April 2025: the pre-treatment coefficients are individually indistinguishable from zero and display no trend. The absence of anticipation is informative about what the shock captures. Trade policy uncertainty had been rising for months before the announcement (Figure D.1), yet lending by more- relative to less-exposed banks did not diverge until tariffs were announced.

The response is therefore tied to the policy change itself rather than to the preceding rise in uncertainty alone, although, as discussed at the start of this section, the estimates

Table 6: Single- vs Multi-Bank Firms

	(1) Full sample	(2) Multi-bank sample
US exposure (std.) × Post	-1.968***	-2.408***
	(0.702)	(0.884)
Bank controls × Post	Yes	Yes
Bank-Firm fixed effects	Yes	Yes
Country-sector-Firm-size-Time fixed effects	Yes	Yes
Observations	45,214,932	17,580,158
Adjusted R^2	0.966	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Bank exposure to U.S. trade is standardized. Bank controls are the January–June 2024 characteristics listed in Section 3.1 and specialization is defined in Equation (B.1); both enter interacted with the post indicator, which equals one from April 2025 onward. Column (1) includes all firms, column (2) restricts the sample to multi-bank firms as in Table 5. Coefficients are multiplied by 100. Standard errors are clustered by bank and sector.

do not separate the tariff increase from the uncertainty and adjustment that accompanied it. The coefficients turn negative immediately after the announcement and remain close to -2 for most of the period through December 2025, in line with the static estimate. The baseline effect is thus not a short-lived adjustment in the announcement month but a persistent divergence in lending between banks with different exposure.

Single-lender firms. The baseline compares lenders to the same firm and therefore relies only on firms with more than one bank. About four in five firms in the sample borrow from a single bank; they account for roughly a third of committed credit and are predominantly small. Table 6 brings them in by replacing the firm–time fixed effects with country–sector–firm-size–time fixed effects, in the spirit of Degryse et al. (2019): credit demand is then held fixed across observably similar firms rather than within the same firm, a weaker control that allows the comparison to include every borrower. Column (2) applies this specification to the multi-bank sample and yields -2.41, somewhat larger than the baseline but within one standard error of it, so the coarser demand control does not overturn the within-firm estimate. Column (1) adds the 27 million single-lender observations and gives -1.97, close to the baseline. The response is therefore not confined to firms that can be compared across lenders, and single-lender firms respond by a similar amount. Because these firms are mostly micro and small enterprises, this result indicates that the contraction reaches the borrowers with the typically fewest alternative lenders.

3.3. Heterogeneity

The average response leaves two distinct questions: which banks account for the contraction, and where within their portfolios do the cuts fall? The bank-side evidence points to a nonlinear exposure response that is weaker at larger banks and stronger when a bank is relatively specialized in the borrower's sector. The borrower-side evidence is different. Direct sector exposure barely changes the response, whereas the contraction is largest in relationships with micro firms. Thus, bank exposure determines which lenders contract; borrower size helps determine where the cuts fall, while the borrower's own sector exposure does not.

Nonlinearity and bank size. Table 7 first asks whether the linear baseline masks differences across the bank-exposure distribution. Adding squared bank exposure in column (2) produces a negative and precisely estimated coefficient of -1.62: the post-shock exposure gradient becomes more negative as exposure rises. The median split in column (3) points in the same direction. Above the median, the exposure slope is an additional 2.68 percentage points more negative than below it, although this difference is estimated only at the 10 percent level. These specifications document curvature toward the upper end of the distribution; they do not identify a sharp threshold. They are therefore reduced-form counterparts to, rather than direct estimates of, the threshold in Section 4.

Bank size moderates this response. The positive interaction with log assets in column (4) implies that the negative exposure gradient is weaker among larger banks. In the joint specification in column (6), both the squared-exposure coefficient (-1.69) and the size interaction (0.69) are virtually unchanged. This pattern is consistent with larger banks having greater capacity to absorb portfolio pressure. Size is not, however, a direct measure of spare intermediation capacity and may also capture differences in funding, diversification, or business model.

Bank–sector specialization. The response also varies with a bank's relative specialization in the borrower's sector. In column (5) of Table 7, the interaction between exposure and specialization is -1.80 and significant at the 5 percent level. It falls to -1.16 in the joint specification and is then significant at the 10 percent level. Table C.1 probes what this interaction captures. It remains negative when the bank's raw sector share is included and when the nonlinear exposure response is added. By contrast, the interactions with the raw sector share and relationship intensity are imprecisely estimated. The pattern is therefore more closely associated with a bank's relative overweight in the borrower's

Table 7: Exposure Nonlinearity and Bank Characteristics

	(1) Baseline	(2) Quadratic	(3) Above median	(4) Bank size	(5) Specialization	(6) Joint
US exposure (std.) × Post	-1.871***	-0.608	-2.025	-2.945***	-1.222*	-1.207
	(0.702)	(0.653)	(1.337)	(0.805)	(0.732)	(0.760)
Squared U.S. exposure (std.) × Post		-1.618***				-1.691***
		(0.423)				(0.397)
US exposure (std.) × Post × above-median bank exposure			-2.679*			
			(1.413)			
US exposure (std.) × Post × log assets				0.691**		0.690**
				(0.345)		(0.346)
US exposure (std.) × Post × bank specialization					-1.804**	-1.163*
					(0.727)	(0.678)
Bank controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,754,847	17,754,847	17,754,847	17,754,847	17,754,847	17,754,847
Adjusted R^2	0.960	0.960	0.960	0.960	0.960	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Column (1) reproduces the baseline; column (2) adds squared bank exposure; column (3) allows the exposure slope to differ above the bank-exposure median; columns (4) and (5) interact the exposure slope with log assets and bank–sector specialization, respectively; and column (6) includes the squared term and both interactions. Bank exposure is standardized. All specifications include bank–firm and firm–time fixed effects, as well as the predetermined bank controls and bank–sector specialization interacted with the post indicator. The post indicator equals one from April 2025 onward. Coefficients are multiplied by 100. Standard errors are clustered by bank and sector. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

sector than with the size of that sector position alone.

This result does not distinguish why specialization matters. Information acquired through sector expertise or relationship lending may help a bank target cuts, while an overweight sector may make those cuts release more intermediation capacity. Valuable relationship rents can instead protect borrowers. The estimates show that the exposure gradient is steeper in specialized relationships; they do not separate these forces or other features of bank–firm matching.

Borrower exposure and firm size. Figure 3 and Table C.2 turn to the borrower side of the relationship. For firms in sectors below the median of U.S. trade exposure, a one-standard-deviation increase in bank exposure is associated with 1.80 percent less committed credit after the shock. The corresponding estimate for firms in above-median sectors is 1.96 percent. The difference between them is -0.17 percentage points, with a standard error of 0.71. Exposed banks therefore contract even when the borrower's own sector has little direct exposure to U.S. trade, and they do not contract detectably more in highly exposed sectors. This is the central cross-borrower pattern formalized in Equation (10): portfolio pressure follows the lender across its borrowers. It does not imply that a firm's own trade exposure is irrelevant to its total borrowing or performance; such firm-level effects are absorbed by the firm–time fixed effects.

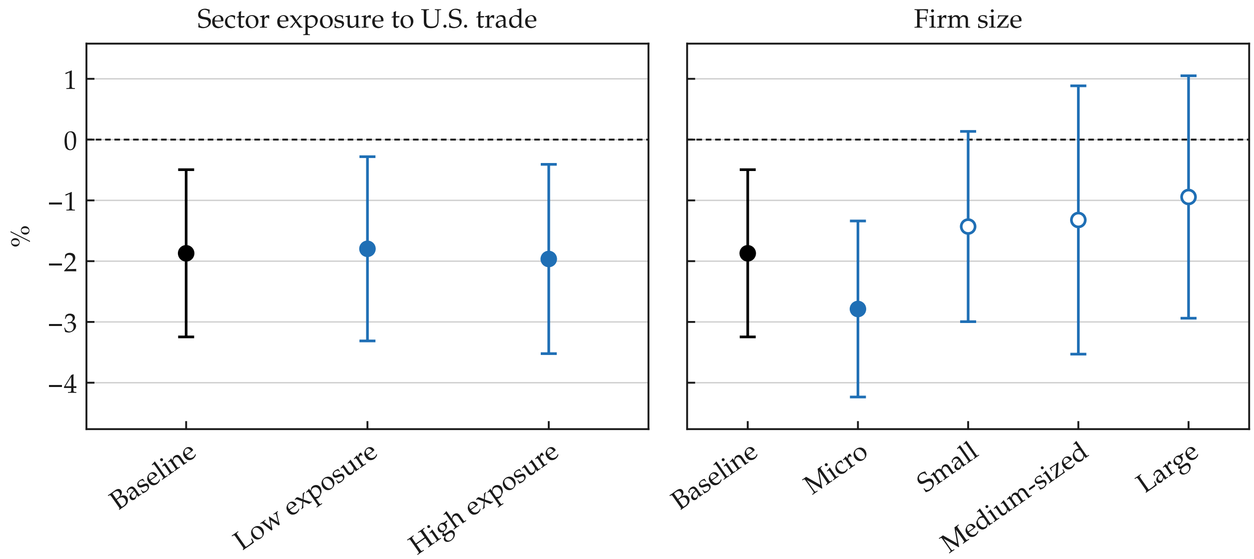


Figure 3: Heterogeneity across Borrower Types

Notes: The figure reports group-specific coefficients on standardized bank exposure interacted with the post indicator, multiplied by 100. Whiskers show 95 percent confidence intervals. The left panel splits borrowers at the median of their sector's U.S. trade exposure; the right panel splits them by firm size. All specifications include bank–firm and firm–time fixed effects, as well as the predetermined bank controls and bank–sector specialization interacted with the post indicator. Standard errors are clustered by bank and sector.

Firm size does matter. The group-specific estimates decline monotonically in absolute value, from −2.79 percent for micro firms to −0.94 percent for large firms. The micro–large difference is 1.84 percentage points and is significant at the 5 percent level; the group-specific large-firm estimate is itself imprecise. The ordering is economically suggestive, but the regressions do not provide a joint test of monotonicity. Moreover, these estimates describe relative commitments by a firm's different lenders within continuing relationships, not the change in its total bank credit. Because smaller firms have fewer lenders ex ante (Table 3), the larger cut to micro-firm relationships raises the possibility that they are less able to replace withdrawn commitments. Appendix A.4 formalizes that margin, but establishing it empirically requires the firm-level outcomes examined below.

Taken together, the heterogeneity results strengthen the portfolio interpretation while delimiting it. The response becomes steeper as bank exposure rises, is attenuated at larger banks, and reaches borrowers outside directly exposed sectors, with the largest relative cut among micro firms. The evidence does not reveal which particular capital, funding, or liquidity constraint binds, nor does it establish an effect on firms' total credit. It shows more narrowly that the exposure-induced contraction is a lender-level phenomenon whose incidence across relationships varies with borrower size.

4. A Simple Model of Bank Credit Allocation

The empirical results reveal two margins of adjustment. On the bank side, the contraction becomes steeper as portfolio exposure rises and is weaker at larger banks. Within a bank's portfolio, the contraction reaches firms in both low- and high-exposure sectors, but is larger for micro firms and in sectors in which the bank is relatively specialized. This section develops a simple model that puts these findings in a common framework. The trade shock first creates pressure at the bank level; the bank then decides where in its portfolio to release intermediation capacity. This separation between the size of the bank shock and the incidence of the resulting cuts is the model's central feature.

The mechanism combines scarce intermediary capital and liquidity (Holmström and Tirole, 1997; Kashyap et al., 2002) with the allocation of lender shocks across borrowers (Khwaja and Mian, 2008; Giannetti and Saidi, 2019; De Jonghe et al., 2020; Iyer et al., 2022). It applies these ideas to trade shocks embedded in bank portfolios (Mayordomo and Rachedi, 2022; Federico et al., 2025a; Correa et al., 2026). The model is a partial-equilibrium interpretation of the evidence, not a structural model of tariff incidence. Appendix A provides the derivations and extensions.

4.1. Setup and solution

Timing and portfolio exposure. There are two dates. At date 0, bank b has a set of borrowers and has promised firm i a commitment $\bar{L}_{ib}$. At date 1, the trade-policy shock arrives and banks revise their commitments. Firms can subsequently seek replacement credit from other lenders.

Let $g(i)$ denote firm i's country–sector cell. Define $x_i \geq 0$ as the predetermined FIGARO exposure assigned to $g(i)$ in Equation (1). Let $\bar{L}_b = \sum_i \bar{L}_{ib}$ denote total initial commitments, and let $\omega_{ib} = \bar{L}_{ib}/\bar{L}_b$ denote the firm's initial portfolio weight. Bank b's portfolio exposure is

$$E_b = \sum_i \omega_{ib} x_i. \tag{5}$$

This is the model counterpart of the credit-weighted FIGARO measure in Equation (2). A shock of severity $\tau > 0$ absorbs $\chi\tau\bar{L}_b E_b$ units of the bank's intermediation capacity. The scale parameter $\chi > 0$ converts trade exposure into units of that capacity. The resulting demand on intermediation capacity can arise from expected losses, provisions, risk-weighted assets, or prospective credit-line drawdowns. These are distinct accounting objects; the model deliberately does not take a stand on which one binds. The initial portfolio determines the hit, so it is fixed when the bank reallocates credit at date 1.

Consider a bank whose trade-exposed manufacturers are expected to draw existing credit lines or require larger provisions. A local service firm need not be exposed to the shock, yet its commitment uses the same intermediation capacity and may be cut when the bank reallocates.

Before the shock, bank b has $S_b \geq 0$ units of spare intermediation capacity. The shock can therefore be absorbed without changing commitments when $\chi\tau\bar{L}_b E_b \leq S_b$; otherwise, the bank must obtain relief from its portfolio.

The bank's problem. Write $q_{ib} = L_{ib}/\bar{L}_{ib}$ for the commitment after the shock relative to its initial level. Moving a relationship away from its initial scale costs $\kappa_{ib}(q_{ib}-1)^2/2$, where $\kappa_{ib} > 0$. A one-euro reduction in credit to firm i releases $c_{ib} > 0$ units of intermediation capacity. The parameters c_{ib} and κ_{ib} may vary with borrower and relationship characteristics, but their ratio does not vary with the borrower's own trade exposure. This benchmark restriction is disciplined by the borrower-sector results rather than imposed as a general property of bank lending. The bank solves

$$\begin{aligned} \min_{\{q_{ib}\}_i} \quad & \sum_i \bar{L}_{ib} \frac{\kappa_{ib}}{2}(q_{ib}-1)^2 \\ \text{subject to} \quad & \sum_i \bar{L}_{ib} c_{ib}(q_{ib}-1) + \chi\tau\bar{L}_b E_b \leq S_b, \qquad q_{ib} \geq 0. \end{aligned} \tag{6}$$

The common constraint is essential: the pressure generated by one set of borrowers absorbs intermediation capacity that the bank also uses to lend to the rest of the portfolio. The quadratic objective is only a convenient way to capture the cost of cutting individual relationships. Any strictly convex adjustment cost yields the same local allocation logic.

Let $\mu_b \geq 0$ denote the shadow cost of intermediation capacity. For an interior relationship, the optimal commitment is

$$q^*_{ib} = 1 - \frac{c_{ib}}{\kappa_{ib}}\mu_b. \tag{7}$$

The bank-level shadow cost μ_b is common to all of the bank's borrowers. The ratio c_{ib}/κ_{ib} determines how strongly a particular relationship responds: cuts are larger where they release more intermediation capacity or are less costly to the bank.

Define normalized spare capacity as $s_b = S_b/\bar{L}_b$. If all relationships remain interior, the shadow cost is

$$\mu_b = \phi_b \left[\chi\tau E_b - s_b\right]_+, \qquad \phi_b = \frac{\bar{L}_b}{\sum_i \bar{L}_{ib} c_{ib}^2 / \kappa_{ib}}, \tag{8}$$

where $[z]_+ = \max\{z, 0\}$. The bank's constraint begins to bind at

$$E_b^* = \frac{s_b}{\chi\tau}. \tag{9}$$

Exposure governs the bank-wide contraction. The relationship-specific ratio c_{ib}/κ_{ib} determines where it falls.

Illustrative parameters. Figure 4 uses normalized units. In panel (a), we set $\chi\tau = 1$ and $(c_{ib}/\kappa_{ib})\phi_b = 1$, so the plotted response is $q_{ib}^* - 1 = -[E_b - s_b]_+$. We compare $s_L = 0.34$ with $s_H = 0.66$. In panel (b), we fix $\mu_b = 0.34$, set $c_{ib} = 1 + 0.75 Z_{b,s(i)}$, and use $\kappa_{ib} = 0.90$ for micro firms and 1.55 for large firms. These values place both thresholds inside the plotted exposure range and keep every commitment positive. They are not empirical estimates. The qualitative patterns require only $s_H > s_L$, a positive association between specialization and c_{ib}, and a lower adjustment cost for micro firms; the particular numbers determine the scale of the illustration, not its ordering.

4.2. Relation to the empirical results

Nonlinearity and bank size. Panel (a) of Figure 4 illustrates the bank-side margin. Below E_b^*, spare capacity absorbs the shock and commitments do not respond. Above it, the shadow cost rises with exposure and lending falls. This occasionally binding constraint produces curvature toward the upper end of the exposure distribution, consistent with the negative squared-exposure coefficient of −1.62 in Table 7; it remains −1.69 in the joint specification. These estimates do not locate a discrete threshold. The quadratic specification and median split instead provide reduced-form descriptions of the curvature.

Greater spare capacity shifts the threshold to the right. The weaker exposure gradient at larger banks is consistent with larger institutions having more ways to absorb the shock—through funding access, internal reallocation, or a larger buffer—or a lower ϕ_b. Total assets are not a direct measure of spare capacity, so the positive size interaction of 0.69 supports this interpretation without identifying the underlying margin.

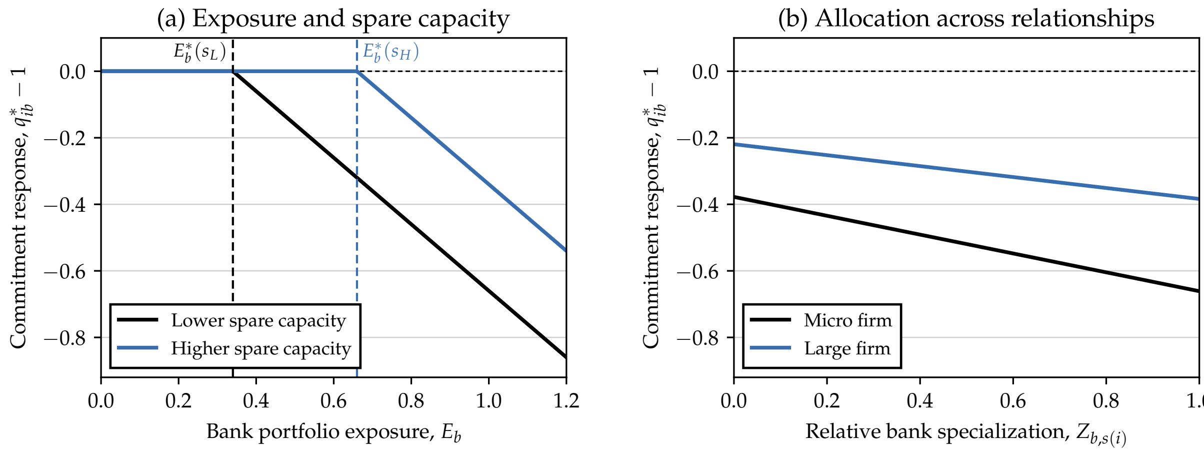


Figure 4: Portfolio Exposure and the Allocation of Credit Cuts

Notes: The figure plots the model's closed-form commitment rule in normalized units. Panel (a) sets $\chi\tau = 1$ and $(c_{ib}/\kappa_{ib})\phi_b = 1$, with $s_L = 0.34$ and $s_H = 0.66$; dashed lines mark the resulting thresholds. Panel (b) sets $\mu_b = 0.34$, $c_{ib} = 1 + 0.75Z_{b,s(i)}$, and $\kappa_{ib} = 0.90$ for micro firms and 1.55 for large firms. All plotted commitments remain positive. The values illustrate the comparative statics and are neither estimates nor a calibration.

Transmission across borrowers. For a bank above its threshold, holding its portfolio composition fixed,

$$\frac{\partial \log L_{ib}^*}{\partial E_b} = -\frac{c_{ib}\phi_b\chi\tau}{\kappa_{ib}q_{ib}^*} < 0. \tag{10}$$

The focal firm's own trade exposure x_i does not appear in this expression. It helped determine the bank's predetermined portfolio exposure in Equation (5), but, once the bank-level pressure has arisen, the benchmark allocation depends on the common shadow cost and relationship characteristics. This distinction maps directly to Table C.2: the exposure gradients are −1.80 and −1.96 for borrowers in low- and high-exposure sectors, respectively, and their difference is statistically insignificant. Because the empirical comparison holds the firm and month fixed, the result is not a statement that the firm's own trade exposure is irrelevant to its demand or performance. It shows that direct exposure is not needed for the lender-side contraction to reach the firm.

Specialization and firm size. Panel (b) illustrates the allocation margin. In the model, the relevant object is c_{ib}/κ_{ib}, not specialization or firm size by themselves. A bank may obtain more relief by cutting an overweight sector if doing so reduces concentration pressure, raising c_{ib}. Information acquired through sector expertise or relationship lending may also help the bank identify commitments that can be scaled back with less disruption, lowering κ_{ib}. Valuable continuation rents work in the opposite direction by protecting a relationship from cuts. The negative exposure–specialization interaction in Tables C.1 and 7 is -1.80 on its own and -1.16 in the joint specification. In the language of the model, the estimate is consistent with a larger effective c_{ib}/κ_{ib} in specialized relationships: the gains from releasing capacity and using information dominate relationship protection on net. It does not distinguish among these channels. This interpretation matches the dual role of specialization emphasized in the banking literature (Iyer et al., 2022).

The firm-size estimates admit the same disciplined reading. The exposure gradient falls in magnitude from -2.79 for micro firms to -0.94 for large firms; the micro–large difference is 1.84 percentage points. This pattern is consistent with a larger effective c_{ib}/κ_{ib} for micro-firm relationships. It could reflect weaker relationship protection, less bargaining power, or more intermediation capacity released per euro cut. The model does not select among these explanations, and it does not generate the empirical size ranking without this relationship-level heterogeneity. In particular, the result should not be described as a generic prediction that banks always cut smaller firms first.

4.3. Extensions and limitations

Persistence. The event-study contraction remains close to 2 percent through December 2025. The static model can accommodate this persistence if the intermediation-capacity use created by the shock adjusts slowly. Appendix A.3 lets that capacity use decay over time: commitments remain below their initial level while it exceeds the bank's spare capacity. This extension organizes the dynamic pattern but does not identify the adjustment rate or the constraint that generates it.

From relationship cuts to firm credit. The baseline coefficient identifies relative credit supply across a firm's lenders, not the change in the firm's total bank credit. After an incumbent cut D_i, the firm may replace credit at alternative lenders. In Appendix A.4, the residual shortfall is decreasing in the number and responsiveness of those alternatives. Micro firms have fewer lenders ex ante (Table 3), so they may face both a larger initial cut and fewer opportunities to replace it. The lender-level estimates alone do not establish that second step.

The model therefore rationalizes a narrow set of findings: nonlinear pressure at exposed banks, transmission to borrowers outside directly exposed sectors, and heterogeneous incidence across relationships. It does not identify which specific capital, funding, or liquidity resource binds, why specialization changes the allocation of cuts, or the aggregate effect on firm credit and investment.

5. Conclusion

The April 2025 U.S. trade-policy shock was followed by a differential contraction in committed lending by euro area banks with more exposed pre-shock borrower portfolios. A one-standard-deviation increase in lender exposure is associated with about 1.9 percent less committed credit after the announcement, relative to another bank serving the same firm in the same month. The differential appears immediately and persists through December 2025. Because the estimates compare continuing relationships within a firm, they identify a relative intensive-margin lender response rather than the change in the firm's total bank credit.

The heterogeneity results clarify how to interpret this response. The exposure gradient becomes steeper toward the upper end of the bank-exposure distribution and is weaker at larger banks, patterns consistent with differences in banks' ability to absorb portfolio pressure. Within portfolios, exposed banks reduce commitments similarly in sectors with low and high U.S. trade exposure, while the contraction is larger for micro firms and relatively specialized relationships. Taken together, these findings support a portfolio channel in which exposure determines the pressure on a lender and relationship characteristics shape the allocation of its cuts.

The results imply that firms' direct trade exposure gives an incomplete picture of how trade-policy shocks affect bank lending. Combining input–output data with credit registers can reveal relevant concentrations in lenders' borrower portfolios and inform the surveillance of trade and geopolitical risks. Whether the relationship-level cuts reduce firms' total credit, investment, or employment—and how access to alternative lenders or monetary conditions affects that pass-through—requires additional evidence.

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Online Appendix

Exposure to Trade Shocks and Bank Lending

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A. Model Details and Extensions

This appendix derives the bank's commitment rule and the comparative statics in Section 4. It then develops the persistence extension and describes the replacement-credit problem relevant for firm-level outcomes.

A.1. Bank problem and solution

The Lagrangian for Equation (6) is

$$\begin{aligned}\mathcal{L}_b = &\sum_i \bar{L}_{ib}\frac{\kappa_{ib}}{2}(q_{ib}-1)^2 \\ &+ \mu_b\left[\sum_i \bar{L}_{ib}c_{ib}(q_{ib}-1) + \chi\tau\bar{L}_b E_b - S_b\right] - \sum_i \bar{L}_{ib}\zeta_{ib}q_{ib},\end{aligned}$$

where $\mu_b \geq 0$ is the shadow cost of intermediation capacity and $\zeta_{ib} \geq 0$ is the multiplier on $q_{ib} \geq 0$. The first-order and complementary-slackness conditions are

$$\begin{aligned}\kappa_{ib}(q_{ib}-1) + c_{ib}\mu_b - \zeta_{ib} &= 0, \\ \mu_b\left[S_b - \sum_i \bar{L}_{ib}c_{ib}(q_{ib}-1) - \chi\tau\bar{L}_b E_b\right] &= 0, \\ \zeta_{ib}q_{ib} &= 0.\end{aligned}$$

Together they imply

$$q^*_{ib} = \max\left\{0, 1 - \frac{c_{ib}\mu_b}{\kappa_{ib}}\right\}. \tag{A.1}$$

For the local comparative statics used in the main text, all relationships are interior and Equation (A.1) reduces to Equation (7).

If the capacity constraint is slack, $q^*_{ib} = 1$ for every relationship and $\mu_b = 0$. If it binds and all relationships are interior, substituting the commitment rule into the constraint yields

$$\begin{aligned}\mu_b &= \frac{\chi\tau\bar{L}_b E_b - S_b}{\sum_i \bar{L}_{ib}c^2_{ib}/\kappa_{ib}} \\ &= \phi_b\left[\chi\tau E_b - s_b\right]_+, \qquad \phi_b = \frac{\bar{L}_b}{\sum_i \bar{L}_{ib}c^2_{ib}/\kappa_{ib}},\end{aligned} \tag{A.2}$$

which proves Equation (8). With relationship-level corners, the shadow cost remains unique because aggregate capacity use is continuous and weakly decreasing in μ_b, but the set of active relationships must be determined jointly with the multiplier.

A.2. Portfolio transmission

Suppose the bank is above its threshold, so that $\chi\tau E_b > s_b$. Holding s_b and ϕ_b fixed,

$$\frac{\partial \mu_b}{\partial E_b} = \phi_b \chi \tau > 0. \tag{A.3}$$

Because $L^*_{ib} = \bar{L}_{ib} q^*_{ib}$, differentiating the interior commitment rule then gives

$$\frac{\partial \log L^*_{ib}}{\partial E_b} = -\frac{c_{ib}}{\kappa_{ib} q^*_{ib}} \frac{\partial \mu_b}{\partial E_b} = -\frac{c_{ib} \phi_b \chi \tau}{\kappa_{ib} q^*_{ib}} < 0, \tag{A.4}$$

which proves Equation (10).

The focal firm's own exposure does not enter Equation (A.4). The benchmark deliberately isolates the portfolio channel: the trade shock creates capacity use through commitments fixed before the shock, and the bank subsequently decides where in its portfolio to release intermediation capacity. Direct changes in the firm's demand for credit are held fixed in the empirical comparison by firm–time effects. A leave-one-firm or leave-one-country–sector version of E_b gives an especially sharp empirical counterpart because it removes the focal borrower from the portfolio shock, but it is not required for the theoretical cross-borrower result.

Relationship-level incidence. A single relationship is small enough that variation in c_{ib}/κ_{ib} has a negligible effect on the bank-wide term ϕ_b. Conditional on μ_b, its commitment cut increases in this ratio. Specialization can affect both primitives: concentration pressure can raise the capacity released by a cut, c_{ib}, while information acquired through sector expertise or relationship lending can lower κ_{ib} by helping the bank target cuts. Relationship continuation value can instead protect a borrower, as the next extension makes explicit. The reduced-form interaction identifies the net effect of these forces, not any one of them separately.

Relationship continuation values. The bank may lose $v_{ib}(\tau) \geq 0$ for each unit by which it cuts a valued relationship. Adding $\sum_i \bar{L}_{ib} v_{ib}(\tau)(1 - q_{ib})$ to the objective and imposing $q_{ib} \leq 1$ gives

$$q^*_{ib} = \max\left\{0, \min\left\{1, 1 + \frac{v_{ib}(\tau) - c_{ib}\mu_b}{\kappa_{ib}}\right\}\right\}.$$

The bank cuts the relationship only when the common capacity cost exceeds its continuation value, $c_{ib}\mu_b > v_{ib}(\tau)$. A high continuation value can therefore offset the portfolio channel for a particular borrower, but it does not eliminate the common shadow-cost term. The benchmark omits this force because our main result concerns the differential response across lenders to the same firm.

Direct borrower exposure. The benchmark holds c_{ib}/κ_{ib} fixed with respect to the focal firm's trade exposure. If lending to an exposed borrower consumes more capacity at the margin, then c_{ib} can increase with x_i; if the shock changes the value of preserving that relationship, then $v_{ib}(\tau)$ can also depend on x_i. Either extension creates a direct borrower-exposure term in addition to the common portfolio channel. The nearly identical empirical gradients across the two borrower-exposure groups motivate excluding that term from the benchmark, but do not imply that it is zero in every setting.

A.3. Persistence

Let the intermediation-capacity use created by the initial trade shock evolve according to

$$u_{b,t+h} = \rho_u^h \chi \tau E_b, \qquad 0 \leq \rho_u < 1, \tag{A.5}$$

where slow-moving provisions, risk weights, expected losses, or drawdown needs can make ρ_u large. Repeating the static allocation problem at each date gives

$$\mu_{b,t+h} = \phi_b \left[u_{b,t+h} - s_b \right]_+ . \tag{A.6}$$

The lending response persists while shock-induced capacity use exceeds spare capacity. This extension rationalizes persistence without treating the event-study path as a separate structural object or assigning a structural interpretation to ρ_u.

A.4. Replacement credit

The baseline estimates compare a firm's lenders and therefore identify relative lender supply, not the change in the firm's total credit. Let $D_i \geq 0$ be the commitment loss imposed by constrained incumbent lenders. Firm i can obtain replacement credit $e_{ib} \geq 0$ from lenders in $\mathcal{A}_i$. Suppose lender b faces a convex expansion cost $\kappa_{ib}^S e_{ib}^2/2$, passed through to the firm through its credit supply schedule, and the firm incurs a quadratic cost $\nu_i G_i^2/2$ from the residual shortfall $G_i = D_i - \sum_{b \in \mathcal{A}_i} e_{ib}$. The resulting problem is

$$\min_{\{e_{ib} \geq 0\}} \frac{\nu_i}{2} \left(D_i - \sum_{b \in \mathcal{A}_i} e_{ib} \right)^2 + \sum_{b \in \mathcal{A}_i} \frac{\kappa_{ib}^S}{2} e_{ib}^2, \quad \sum_{b \in \mathcal{A}_i} e_{ib} \leq D_i. \tag{A.7}$$

For an interior solution, the first-order condition is $e_{ib} = \nu_i G_i / \kappa_{ib}^S$. Define the aggregate responsiveness of alternative credit supply as

$$H_i = \sum_{b \in \mathcal{A}_i} \frac{1}{\kappa_{ib}^S}.$$

Summing the first-order conditions and using the definition of G_i gives

$$G_i = \frac{D_i}{1 + \nu_i H_i}, \qquad \Omega_i \equiv 1 - \frac{G_i}{D_i} = \frac{\nu_i H_i}{1 + \nu_i H_i}, \tag{A.8}$$

where Ω_i is the share of the initial cut replaced elsewhere. Firms with few alternative lenders, or with alternatives that are themselves constrained, have lower H_i and bear more of the lender-level contraction.

A.5. Scope

FIGARO maps the tariff shock into predetermined country–sector exposure before the bank portfolio transmits it across borrowers. A full production-network model would additionally allow the credit response to feed back into customers and suppliers. The present model treats x_i as a sufficient exposure index because the firm-level production links and parameters needed for those feedbacks are not observed.

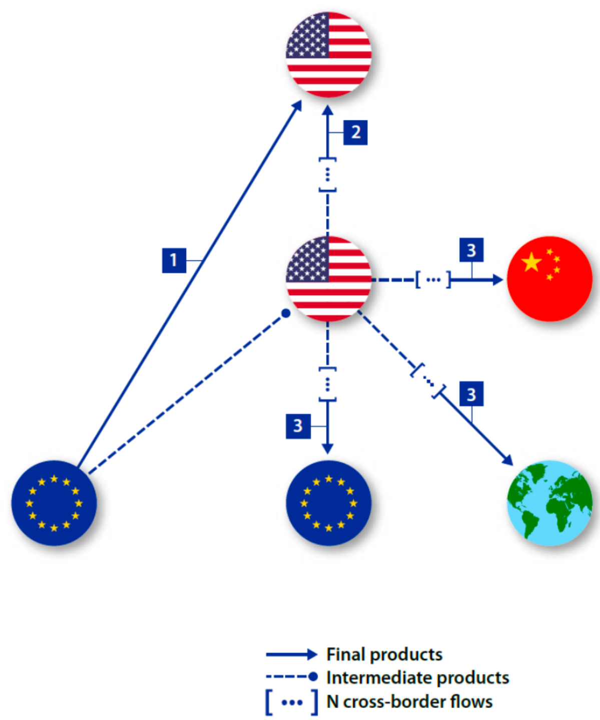
B. Data

B.1. FIGARO Exposure Definitions

In this appendix, we briefly discuss three related but distinct measures of U.S. trade exposure. These indicators are drawn from the Macroeconomic Globalisation Indicators based on FIGARO.[1]

[1] Eurostat dataset `naio_10_fg`, "Macroeconomic globalisation indicators based on FIGARO"; see Eurostat (2024) for the methodology.

Figure B.1: Domestic value added in exports



Notes: Infographic illustrating the definition of domestic value added in exports. Source: European Commission (2024).

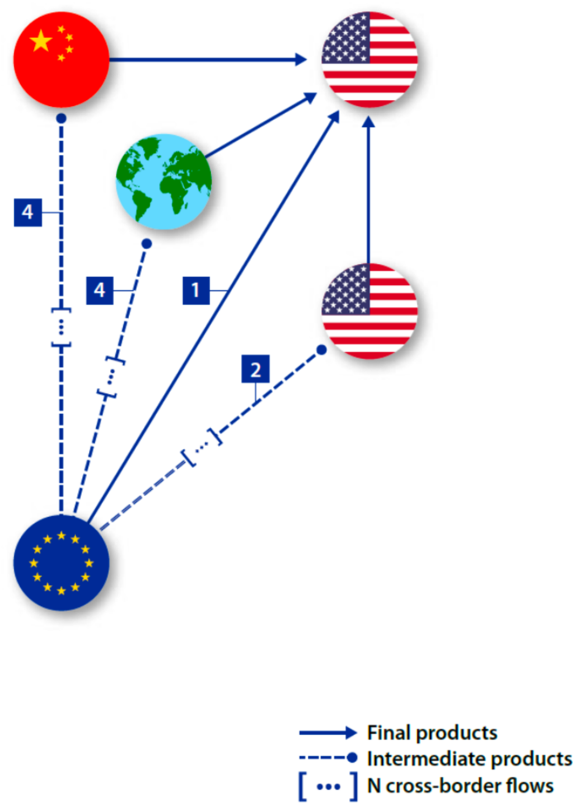
B.1.1. Domestic value added in exports

Domestic value added in exports measures the gross value added generated within the exporting economy as a result of its exports. It includes both the value added by the exporting industry and the indirect value added from upstream domestic suppliers. Compared to gross exports, this indicator more accurately reflects a country's economic gain from trade, as gross export values include foreign inputs and therefore overstate domestic contributions.

B.1.2. Domestic value added in foreign final use

Domestic value added in foreign final use is the value created in a country that is ultimately consumed abroad as final demand. It tracks value through the entire global value chain, thereby capturing indirect trade links. It focuses exclusively on foreign final demand in a given country, and excludes intermediate exports that are not ultimately absorbed in that country. The indicator reflects global demand exposure.

Figure B.2: Domestic value added in foreign final use



Notes: Infographic illustrating the definition of domestic value added in foreign final use. Source: European Commission (2024).

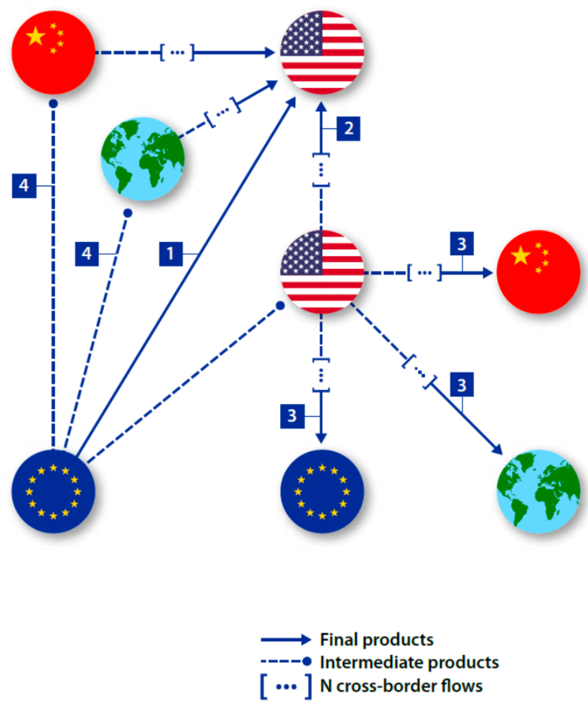
B.1.3. Trading partner exposure

Trading partner exposure gives a single comprehensive metric of how exposed an EU country's value added generation is to a specific trading partner. Neither domestic value added in exports nor domestic value added in foreign final use fully captures all channels of dependence, which is why this indicator combines elements of both. Specifically, it accounts for four types of trade flows:

1. Direct exports of final goods to the partner (e.g., EU exports a finished product directly to the US for consumption)

2. Intermediate exports to the partner that end up consumed within that partner's economy (e.g., EU ships components to the US, which are assembled and consumed in the US)

Figure B.3: Trading partner exposure



Notes: Infographic illustrating the definition of trading partner exposure. Source: European Commission (2024).

3. Intermediate exports to the partner that are further re-exported to third countries for final use (e.g., EU components go to the US, the US incorporates them into goods exported to China)

4. Intermediate exports to third countries that eventually feed into the partner's final consumption (e.g., EU exports components to China, China uses them in goods it sells to the US)

As such, trading partner exposure captures both direct and indirect exposure of a country's value added to a partner's demand, across final goods and intermediate products throughout the entire global value chain.

B.2. Country-Sector Trade Exposures

The data used to construct the trade exposure measures are disaggregated at the NACE two-digit level. In some cases, individual two-digit categories are not reported separately and are instead aggregated with other sectors, e.g. C10-C12. Table B.1 lists the mutually exclusive NACE sectors at the level used in our analysis.

Table B.1: NACE Sections Included in Analysis

Code	Description
A	**Agriculture, forestry and fishing**
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B	**Mining and quarrying**
C	**Manufacturing**
C10–C12	Manufacture of food products; beverages and tobacco products
C13–C15	Manufacture of textiles, wearing apparel, leather and related products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31–C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D	**Electricity, gas, steam and air conditioning supply**

Code	Description
D35	Electricity, gas, steam and air conditioning supply
E	**Water supply; sewerage; waste management and remediation activities**
E36	Water collection, treatment and supply
E37–E39	Sewerage, waste management, remediation activities
F	**Construction**
G	**Wholesale and retail trade; repair of motor vehicles and motorcycles**
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H	**Transportation and storage**
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	**Accommodation and food service activities**
J	**Information and communication**
J58	Publishing activities
J59–J60	Motion picture, video, television programme production; programming and broadcasting activities
J61	Telecommunications
J62–J63	Computer programming, consultancy, and information service activities
K	**Financial and insurance activities**
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities

Code	Description
L	**Real estate activities**
M	**Professional, scientific and technical activities**
M69–M70	Legal and accounting activities; activities of head offices; management consultancy activities
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74–M75	Other professional, scientific and technical activities; veterinary activities
N	**Administrative and support service activities**
N77	Rental and leasing activities
N78	Employment activities
N79	Travel agency, tour operator and other reservation service and related activities
N80–N82	Security and investigation, service and landscape, office administrative and support activities
O	**Public administration and defence; compulsory social security**
O84	Public administration and defence; compulsory social security
P	**Education**
P85	Education
Q	**Human health and social work activities**
Q86	Human health activities
Q87–Q88	Residential care activities and social work activities without accommodation
R	**Arts, entertainment and recreation**
R90–R92	Creative, arts and entertainment activities; libraries, archives, museums and other cultural activities; gambling and betting activities
R93	Sports activities and amusement and recreation activities
S	**Other services activities**
S94	Activities of membership organisations
S95	Repair of computers and personal and household goods

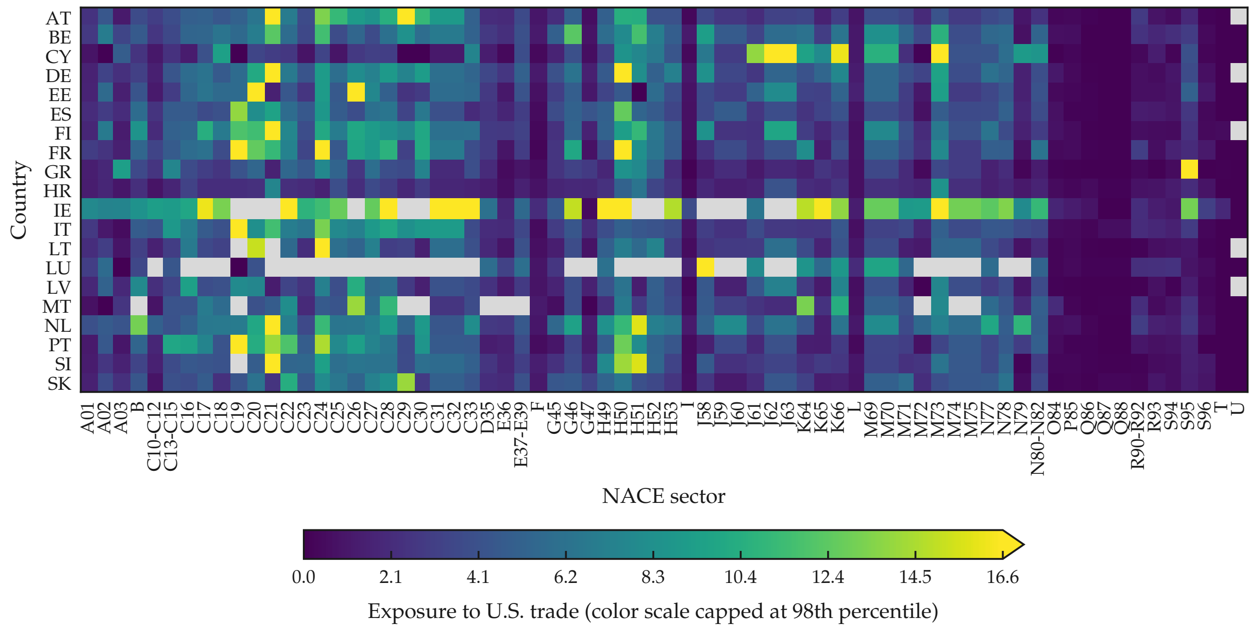


Figure B.4: Distribution of country-sector exposure to U.S. trade

Notes: The figure shows exposure to U.S. trade for each euro area country and NACE Rev. 2 sector in 2023, as defined in Equation (1). The color scale is capped at the 98th percentiles to improve visual differentiation.

Code	Description
S96	Other personal service activities
T	**Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use**
U	**Activities of extraterritorial organisations and bodies**

B.3. AnaCredit Sample Construction

We begin with AnaCredit instrument records for the 20 countries that belonged to the euro area throughout July 2024–December 2025. The table below records the restrictions that define the baseline sample. We aggregate eligible instruments to the bank–firm–month level and apply the borrower and sector restrictions before .

Table B.2: Baseline AnaCredit Sample Definition

Dimension	Baseline definition
Lenders	Euro area deposit-taking corporations (ESA sector S.122) designated on the January 2024 SSM reference list as part of a Significant Institution
Borrowers	Private non-financial corporations not recorded in default, and without a probability of default equal to one, at the initial observation
Sectors	All NACE sectors except for D, E, K, O, T, and U, following Correa et al. (2026)
Credit records	Positive outstanding and committed amounts; drop relationships with committed credit below 50€; main outcome limited to non-revolving credit lines and other loans
Reporting unit	Individual reporting institution; no consolidation to the banking group
Time	January–June 2024 for portfolio construction; July 2024–December 2025 for outcomes, yielding nine pre-shock and nine post-shock months

Notes: The final baseline contains 471 banks, 2,658,995 firms, and 3,409,825 bank–firm relationships. NACE D is electricity and gas; E is water and waste; K is finance and insurance; O is public administration; T is household activities; and U is extraterritorial organizations.

B.4. Variable Definitions

B.4.1. Bank–sector specialization

To separate U.S. trade exposure from sector expertise, we follow Blickle et al. (2023). Let $q_{b,s,t}$ denote sector s's share in bank b's committed-credit portfolio and $q_{s,t}$ its share in aggregate credit. We define bank b's relative specialization in sector s as

$$Z_{b,s} = \log\left(1 + \frac{1}{|\mathcal{T}_0|}\sum_{t\in\mathcal{T}_0}\frac{q_{b,s,t}}{q_{s,t}}\right), \qquad \mathcal{T}_0 = \{\text{January–June 2024}\}. \tag{B.1}$$

A value of $\log(2) = 0.693$ corresponds to a neutral portfolio share; larger values indicate that the bank is overweight in the sector. We assign zero credit to unobserved bank–sector pairs before computing the shares. In the bank–firm regressions, each relationship receives the bank's specialization in the borrower's sector. For the bank-level comparison below, we instead average $Z_{b,s}$ across sectors using each sector's January–June 2024 share in the bank's committed-credit portfolio.

B.5. Additional Descriptive Statistics

Table B.3: Summary Statistics

Variable	Mean	SD	P10	P25	P50	P75	P90	N
Panel A: Bank-firm relationship characteristics (N relationships = 4,248,756)								
Outstanding amount (EUR)	733,935	10,178,002	20,705	35,311	89,250	282,025	925,000	4,248,756
Committed amount (EUR)	802,228	13,149,075	21,577	36,128	92,028	294,064	982,726	4,248,756
Interest rate (annual %)	3.75	2.52	1.10	2.01	3.74	4.95	6.28	4,248,756
Residual maturity (years)	5.41	5.20	0.88	1.92	3.71	6.81	12.95	4,217,846
Probability of default (%)	5.62	15.59	0.18	0.42	1.11	3.24	9.93	2,690,373
Bank-sector specialization	0.92	0.55	0.32	0.57	0.87	1.11	1.49	4,248,756
Panel B: Firm characteristics (N firms = 3,171,231)								
Firm age (years)	15.19	15.09	2.67	5.67	10.62	21.00	33.65	3,171,231
Employees	72.01	7,356.78	0.00	1.00	2.00	8.78	24.00	2,681,238
Number of lenders	1.24	0.91	1.00	1.00	1.00	1.00	2.00	3,171,231
Number of lenders (cond. $N > 1$)	2.48	1.63	2.00	2.00	2.00	2.50	3.44	621,979
Panel C: Bank characteristics (N banks = 1,690)								
Log total assets	7.93	1.67	5.89	6.92	7.78	8.80	10.09	1,689
NFC loan share	0.21	0.14	0.06	0.13	0.19	0.26	0.37	1,689
HH loan share	0.33	0.20	0.01	0.20	0.35	0.47	0.56	1,689
NFC deposit share	0.12	0.09	0.01	0.07	0.10	0.15	0.21	1,689
HH deposit share	0.41	0.23	0.00	0.27	0.45	0.56	0.69	1,689
EA government securities share	0.05	0.08	0.00	0.00	0.01	0.05	0.17	1,689
Panel D: Bank exposure (N banks = 1,690)								
US trade exposure	3.00	1.23	1.62	2.24	2.86	3.58	4.48	1,690
Non-US trade exposure	14.36	7.54	8.46	10.75	13.22	16.56	21.31	1,690
US trade exposure	2.96	1.34	1.58	2.09	2.75	3.57	4.49	1,689
Non-US trade exposure	14.24	8.10	8.10	10.20	12.97	16.67	21.48	1,689
US trade exposure	2.94	1.33	1.55	2.09	2.75	3.56	4.48	1,690
Non-US trade exposure	14.12	7.66	8.08	10.11	12.93	16.65	21.43	1,690

Notes: The table is based on the sample of all banks. Panels A and B report bank–firm relationship and firm characteristics, averaged over the estimation sample period July 2024 – December 2025. The variables that enter the regressions as pre-determined controls – bank characteristics and bank trade exposure (Panels C and D) and bank–sector specialization (Panel A) – are instead averaged over the six months preceding the estimation sample (January – June 2024). The interest rate and residual maturity are outstanding-amount-weighted. Bank–sector specialization refers to a bank's specialization in firm i's sector and is defined as in equation Equation (B.1) with a value of 0.693 corresponding to neutrality. Number of lenders (cond. $N > 1$) refers to number of lenders among firms that have multiple bank relationships. Bank balance-sheet shares are expressed as fractions of total assets. US trade exposure is defined in Equation (2), and non-US trade exposure is computed analogously. Number of observations vary with data availability. For detailed data sources see text in Section 2.

Table B.4: Sample Composition by Firm Age and Size

Firm age	Micro	Small	Medium	Large	Total
Below 6y	22.9	2.1	0.3	0.1	25.4
6–15y	27.4	6.6	1.2	0.5	35.7
16y+	25.5	10.0	2.5	0.8	38.9
Total	75.9	18.7	4.0	1.4	100.0

Notes: Entries are percentages of firms with non-missing age and size. Firm size follows the European Commission definition, which combines employment with balance-sheet size or annual turnover. The table covers 2,459,979 firms, approximately 93 percent of firms in the baseline sample.

C. Additional Empirical Results

C.1. Heterogeneity

Table C.1 reports additional specifications for the bank–sector specialization result. Columns (1)–(4) compare relative specialization with the bank's raw sector share and allow the exposure response to be nonlinear. The interaction with relative specialization remains negative, while the interactions with the raw sector share and relationship intensity are imprecisely estimated. Column (6) also finds no statistically significant difference in the bank-exposure gradient with the borrower's continuous U.S. trade exposure.

Table C.2 reports heterogeneity by borrower-sector exposure and firm size. The exposure gradients are similar for firms in below- and above-median exposure sectors; their difference is small and imprecisely estimated. By firm size, the contraction is largest for micro firms and declines in magnitude from micro to large firms. The micro–large difference is 1.84 percentage points and statistically significant at the 5 percent level.

Table C.1: Bank–Sector Specialization and Alternative Portfolio Measures

	(1) Specialization	(2) Sector share	(3) Both	(4) Quadratic	(5) Relationship intensity	(6) Borrower exposure
US exposure (std.) × Post	-1.222*	-1.949***	-1.439*	0.369	-1.830**	-1.972***
	(0.732)	(0.712)	(0.740)	(0.887)	(0.714)	(0.709)
Squared U.S. exposure (std.) × Post				-1.858***		
				(0.497)		
US exposure (std.) × Post × bank specialization	-1.804**		-2.002***	-1.316**		
	(0.727)		(0.742)	(0.620)		
US exposure (std.) × Post × sector share		-0.167	1.387	-3.082		
		(3.347)	(3.131)	(2.602)		
US exposure (std.) × Post × relationship intensity					-4.902	
					(6.194)	
US exposure (std.) × Post × U.S. trade exposure						-0.123
						(0.112)
Bank controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,754,847	17,754,847	17,839,844	17,754,847	15,578,840	17,689,778
Adjusted R^2	0.960	0.960	0.960	0.960	0.958	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Columns (1)–(4) compare relative bank–sector specialization with the bank's raw portfolio share in the borrower's sector; column (4) also allows for a quadratic exposure response. Column (5) uses relationship intensity, and column (6) interacts bank exposure with the borrower's U.S. trade exposure. Bank exposure is standardized. All specifications include bank–firm and firm–time fixed effects, as well as the predetermined bank controls and bank–sector specialization interacted with the post indicator. The post indicator equals one from April 2025 onward. Coefficients are multiplied by 100. Standard errors are clustered by bank and sector. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.2: Heterogeneity across Borrower Types

	Borrower-sector exposure		Firm size	
	(1)	(2)	(3)	(4)
	Difference	Group effects	Difference	Group effects
US exposure (std.) × Post	-1.797**		-2.787***	
	(0.773)		(0.739)	
US exposure (std.) × Post × Below-median NACE exposure		-1.797**		
		(0.773)		
US exposure (std.) × Post × Above-median NACE exposure	-0.168	-1.964**		
	(0.705)	(0.794)		
US exposure (std.) × Post × Micro firms				-2.787***
				(0.739)
US exposure (std.) × Post × Small firms			1.357*	-1.430*
			(0.699)	(0.799)
US exposure (std.) × Post × Medium-sized firms			1.465*	-1.322
			(0.835)	(1.126)
US exposure (std.) × Post × Large firms			1.843**	-0.944
			(0.842)	(1.018)
US exposure (std.) × Post × Firms of unknown size			1.344	-1.443
			(0.922)	(1.235)
Bank controls × Post	Yes	Yes	Yes	Yes
Bank-Firm fixed effects	Yes	Yes	Yes	Yes
Firm-Time fixed effects	Yes	Yes	Yes	Yes
Observations	17,689,778	17,689,778	17,754,847	17,754,847
Adjusted R^2	0.960	0.960	0.960	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Columns (1) and (3) use the below-median borrower-sector exposure group and micro firms, respectively, as reference groups; the triple interactions report differences from those groups. Columns (2) and (4) report the group-specific exposure slopes. Bank exposure is standardized. All specifications include bank–firm and firm–time fixed effects, as well as the predetermined bank controls and bank–sector specialization interacted with the post indicator. The post indicator equals one from April 2025 onward. Coefficients are multiplied by 100. Standard errors are clustered by bank and sector. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D. Sensitivity Analysis

D.1. Timing and anticipation

Trade policy uncertainty began rising before the April 2, 2025 tariff announcement, while effective tariff rates increased sharply after the announcement (Figure D.1). This earlier rise in uncertainty could have prompted banks to adjust credit before April. The event-study estimates in Figure 2, however, show neither a systematic differential pre-trend nor an anticipatory decline in lending by more-exposed banks.

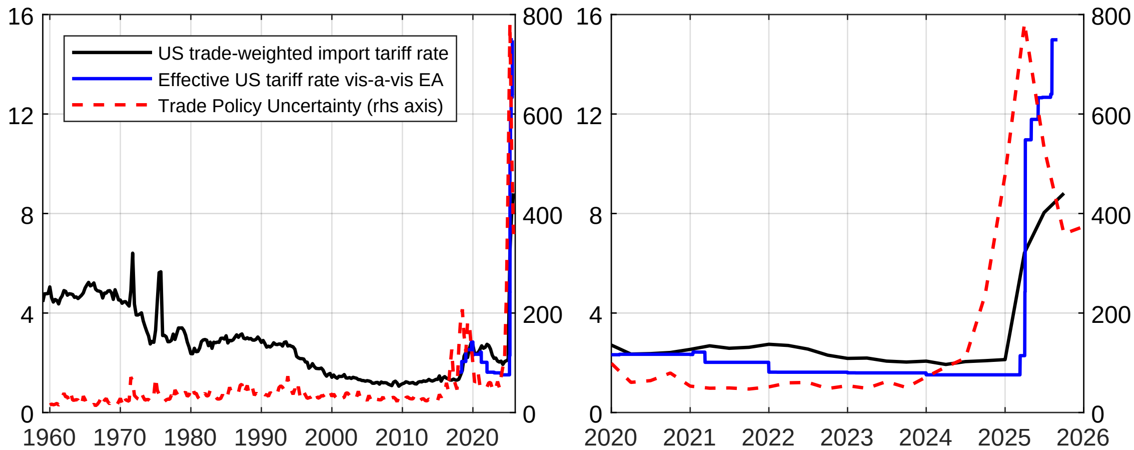


Figure D.1: Tariff rates and trade policy uncertainty

Notes: U.S. effective tariff rates (%) and the trade policy uncertainty index, 1960–2026. The right-hand panel shows the period from 2020 onward.

D.2. Inference and Clustering

Table D.1: Alternative Clustering of Standard Errors

	(1) Bank	(2) Banking group	(3) Bank-country/sector	(4) Bank-firm	(5) Bank-time
US exposure (std.) × Post	-1.871**	-1.871**	-1.871***	-1.871***	-1.871**
	(0.879)	(0.937)	(0.711)	(0.648)	(0.662)
Bank controls	Yes	Yes	Yes	Yes	Yes
Bank controls × Post	Yes	Yes	Yes	Yes	Yes
Bank-Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,754,847	17,754,847	17,754,847	17,754,847	17,754,847
Adjusted R^2	0.960	0.960	0.960	0.960	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Bank exposure to U.S. trade is standardized. Bank controls are the January–June 2024 characteristics listed in Section 3.1; they are interacted with the post indicator, which equals one from April 2025 onward. Coefficients are multiplied by 100. Standard errors are clustered by bank in column (1), banking group (2), bank and country/sector (3), bank and firm (4), and bank and time (5). $^{*}p < 0.10$, $^{**}p < 0.05$,

D.3. Alternative Sample Definitions

Table D.2: Alternative Specifications or Samples

	(1) Lagged controls	(2) Exclude Ireland
US exposure (std.) × Post	-1.922***	-1.856***
	(0.638)	(0.689)
Bank controls (lagged) × Post	Yes	
Bank controls (2024H1 value) × Post		Yes
Exclude Ireland		Yes
Bank-Firm fixed effects	Yes	Yes
Firm-Time fixed effects	Yes	Yes
Observations	17,754,847	17,726,339
Adjusted R^2	0.960	0.960

Notes: The dependent variable is the log committed loan amount at the bank–firm–month level. Bank exposure to U.S. trade is standardized. Bank controls are one-month lagged value of characteristics listed in Section 3.1 for column (1) and the January–June 2024 averaged values for column (2). Ireland is excluded from the sample in column (2). Coefficients are multiplied by 100. Standard errors are clustered by bank and sector. $^{*}p < 0.10$, $^{**}p < 0.05$,

References Appendix

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