Trade Uncertainty and U.S. Bank Lending

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Abstract

This paper uses U.S. credit register data and the 2018–2019 spike in trade uncertainty to study its effects on domestic credit supply. Exploiting cross-bank differences in *ex ante* exposure to trade uncertainty, we show that higher uncertainty is associated with a relative contraction in loan growth to non-financial firms and an increase in loan rates, and that these effects are stronger for lower-capital banks. These findings are consistent with a stylized model in which banks facing binding lending-capacity constraints respond to elevated uncertainty by curtailing credit supply. The resulting contraction in credit has significant real effects, particularly for bank-dependent firms. Firms' exposure to uncertainty through their lenders affects investment above and beyond their direct exposure to uncertainty.

JEL Classifications: G21, F34, F42

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1 Introduction

Recent episodes such as Brexit, the pandemic, and shifts in U.S. trade policy have heightened trade uncertainty and renewed interest in its economic effects. Whereas it is well understood that a rise in uncertainty increases the variance of project returns faced by firms, thereby affecting investment decisions,[1] its implications for financial intermediaries are less clear. In particular, if banks face lending capacity constraints, an increase in uncertainty may tighten those constraints and induce a contraction in credit supply. Such a mechanism differs from shocks to the mean return of borrowers' projects or to bank balance sheets that the literature traditionally emphasizes.[2] Against this backdrop, we ask whether and how trade uncertainty is propagated by banks to the domestic economy, and what this implies about the mechanisms through which uncertainty more broadly affects the supply of bank credit.

To address these questions, we develop testable hypotheses from a stylized model of bank lending to multiple sectors under uncertainty in which banks are capital constrained. The model predicts that banks with greater *ex ante* exposure to trade uncertainty through their loan portfolios contract lending when uncertainty rises, with larger effects for more constrained banks. We then construct a novel measure of banks' exposure to trade uncertainty through their lending portfolios by combining data on firm-level trade uncertainty from Hassan et al. (2019) with comprehensive credit register information on individual loans from the Federal Reserve. Combining this exposure measure with a difference-in-differences (DID) design, we exploit the sharp rise in trade uncertainty during the 2018–2019 escalation of U.S. trade tensions to identify its effects on bank lending.

Our empirical work highlights three main findings. First, banks that are more exposed to trade uncertainty reduce loan commitment growth and raise loan spreads more than less-exposed banks during the 2018–2019 period. These results are economically significant: a one standard deviation change in bank exposure is associated with a credit growth contraction by 6.7 percentage points (ppts) and an increase in spreads by 8.1 basis points (bps). Second, this relative contraction is

[1] There is a well-established literature that studies the real effects of uncertainty. For example, see Bernanke (1983); Pindyck (1991); Caballero and Pindyck (1992); Dixit and Pindyck (1994) for theoretical contributions and Bloom et al. (2007); Bloom (2009); Handley and Limao (2015) for empirical evidence.

[2] See, for example, Peek and Rosengren (2000); Ivashina and Scharfstein (2010); Cornett et al. (2011); Giannetti and Laeven (2012); Chodorow-Reich (2014); Amiti and Weinstein (2018); Mayordomo and Rachedi (2022), and Federico et al. (2025).

concentrated among lower-capital banks. Third, firms whose lenders are more exposed to trade uncertainty reduce debt growth and investment: a one standard deviation increase in firms' indirect exposure to trade uncertainty leads to a 4.1 ppt decline in investment rates. Importantly, this indirect effect of uncertainty on firm behavior holds when controlling for firms' own direct exposure to uncertainty, highlighting the amplification mechanism of our bank exposure to trade uncertainty channel on the real economy.

The 2018–2019 period provides an ideal setting to examine the impact of rising trade-related uncertainty on bank lending. Beginning in 2018, the United States imposed successive rounds of tariffs on imports from major trading partners across a wide range of industries; affected countries retaliated, and the resulting escalation generated substantial uncertainty about the duration of tariffs, the scope of future measures, and the likelihood of further retaliation.[3] This surge in uncertainty—well documented in the literature as the largest in decades at the time (Caldara et al., 2020; Grossman et al., 2024; Hassan et al., 2024)—provides the empirical variation central to our analysis.

We construct our bank exposure measure using firm-level trade uncertainty derived from text analysis of listed firms' quarterly earnings call transcripts (Hassan et al., 2019). Because many bank borrowers are private firms for which firm-specific uncertainty measures are unavailable, we aggregate these measures to the industry level and assign them to borrowers based on their industry classification.[4] A bank's exposure to trade uncertainty is defined as the average change in sector-level uncertainty between 2016–2017 and 2018–2019, weighted by the bank's loan shares across industries (averaged over 2014–2015). Using pre-period loan shares to construct the weights ensures that the exposure measure is predetermined with respect to economic conditions during the sample period. A covariate balance test further shows that exposure is not systematically related to a wide range of observable bank characteristics.

We employ this exposure measure in a standard DID framework that relates lending outcomes—such as the growth in outstanding loan commitments and loan spreads—to banks' *ex ante* exposure

[3] Uncertainty affected not only sectors directly targeted by tariff changes but also other sectors. A notable example is the May 2019 threat to impose a 5% tariff on all Mexican goods, which was ultimately withdrawn following a July 2019 agreement. See Brown and Kolb (2025) for a detailed timeline of the trade war.

[4] We use "sector" and "industry" interchangeably throughout the paper, where "industry" is used when discussing data construction and sources.

to trade uncertainty interacted with a Post indicator equal to one for 2018–2019 and zero for 2016–2017. Our main data source is the supervisory Federal Reserve Y-14Q dataset, which provides detailed information on individual loan commitments for the near universe of commercial loans originated by large U.S. banks. The granularity of these data allows us to control flexibly for time-varying firm credit demand by including firm×quarter fixed effects, following Khwaja and Mian (2008) and Jiménez et al. (2020), and to account for assortative matching in the bank loan market with bank×firm fixed effects (Schwert, 2018). To isolate the impact of trade uncertainty from that of implemented trade policy, all specifications control for banks' exposure to tariffs, measured as the *ex ante* share of their loan portfolio extended to firms in tariff-affected sectors.

Our first result, that an increase in uncertainty is associated with a larger credit contraction for more exposed banks, is consistent with the behavior of banks facing binding lending-capacity constraints: when trade uncertainty rises, the wider dispersion of loan returns tightens banks' capital constraints, inducing them to curtail overall credit supply even in the absence of loan losses. More exposed banks appear more cautious in deploying capital to risky activities, reducing loan growth, charging higher spreads, shortening maturities, and tightening collateral requirements more than other banks. Furthermore, this relative credit contraction holds for *all* of the banks' borrowers, including those that are less directly exposed to an increase in trade uncertainty, because a tighter capital constraint limits a bank's total lending capacity rather than lending to individual sectors.

The second set of results directly tests for a capital constraints channel: exposed banks with lower capital buffers contract their lending more, consistent with our model's insight that capital buffers provide a cushion against tightening Value-at-Risk (VaR) constraints when loan return volatility rises. In addition, more exposed banks are relatively more likely to re-balance their asset allocations away from commercial loans and into safer assets, notably government-backed securities. More exposed banks also assess their borrowers as relatively riskier, raising the probability of default assigned to each borrower, but do not increase loan loss reserves nor do they experience higher loan delinquencies or writedowns. These findings are consistent with lending decisions being driven by a rise in return volatility as opposed to a shift in mean returns, and support our interpretation of uncertainty as a mean-preserving increase in the dispersion of loan returns.

The third set of results focuses on the real effects of the bank credit contraction. A key question is whether firms can substitute away from exposed banks and neutralize the impact on their balance sheets. We find they cannot fully do so: firms that are more exposed to uncertainty through their lenders experience slower debt growth, investment, and asset growth than other firms, with worse outcomes for firms more reliant on bank debt. These results are consistent with banks amplifying the effects of uncertainty on the domestic economy. We also show that while the indirect effect of trade uncertainty on firms through their banks operates broadly across all sectors, firms' direct exposure to trade uncertainty reduces investment only in tariff-hit sectors.

A key identification challenge in isolating the effects of trade uncertainty on credit supply is that both banks' credit supply and firms' credit demand may respond to changes in the trade environment. For example, loan growth could slow if firms in high-uncertainty sectors postpone investment, or increase if those firms build inventories or diversify supply chains. A purely demand-side interpretation, however, is difficult to reconcile with our main finding that more exposed banks exhibit both lower loan growth (quantity) and higher spreads (price). Moreover, the growth rate of utilized loan amounts does not vary systematically with bank exposure to uncertainty, and credit line usage rates are similar for firms in high- and low-uncertainty sectors, providing further evidence against a demand-driven explanation. Finally, to the extent that firm-level demand shifts may correlate with bank specialization patterns that shape lending decisions (Paravisini et al., 2023), we show that our results are robust to a wide range of controls for bank specialization and to finer fixed effects that capture heterogeneity in the types of loans supplied by specialized banks.

A range of additional tests further strengthens the interpretation of our results. First, placebo exercises and dynamic difference-in-differences estimates show no evidence of differential pre-trends in lending outcomes across more- and less-exposed banks, nor in real outcomes across more- and less-exposed firms. Second, the findings remain robust in a sample of newly originated loans and among single-lender firms—the majority of borrowers in the credit register. Third, the results are not driven by banks' exposure to non-tariff policies (such as sanctions), to uncertainty arising from sectors unrelated to trade, to differences in the sensitivity of bank loan portfolios to the business cycle, or to concurrent macroeconomic developments including oil price fluctuations and exchange rate movements. Finally, our conclusions are robust to alternative methodological choices, including different clustering approaches for standard errors and weighted least squares estimation that accounts for variation in the precision of sector-level uncertainty measures.

Related literature. We contribute to two distinct strands of the literature that studies the impact of uncertainty on the economy. The first strand analyzes how uncertainty shapes financial intermediaries' decisions and transmits to the real economy, while the other examines the real effects of uncertainty on firms. The first strand studies how uncertainty affects banks' balance sheets and lending decisions (Buch et al., 2015; Valencia, 2017; Jasova et al., 2021; Wu and Suardi, 2021; Ramcharan et al., 2025). Buch et al. (2015) and Valencia (2017), for example, show that heightened macroeconomic uncertainty leads to a contraction in bank lending, with the magnitude of the response varying systematically across banks depending on bank capitalization. Similar to these studies, our results highlight the central role of capital buffers in shaping the credit supply response to uncertainty shocks, but differ in that we analyze the impact of *sector-specific* uncertainty on bank lending. Jasova et al. (2021) analyze liability-side uncertainty regarding continued access to central bank funding and document a risk-taking channel of lender-of-last-resort policy. In contrast, we study asset-side uncertainty arising from the trade exposure of banks' loan portfolios. Asset-side uncertainty increases the risk of banks' existing assets, tightens financing constraints, and induces a contraction in lending even absent changes in expected returns, accompanied by a reallocation toward safer, government-backed securities. By jointly identifying firms' direct exposure and their indirect exposure through their lenders' portfolio composition, we uncover a distinct amplification channel of uncertainty that links intermediary balance sheets to real outcomes.

The second strand of the literature shows that uncertainty affects firms' investment and risk-taking through option value effects, precautionary behavior, and changes in risk premia (Dixit and Pindyck, 1994; Bloom, 2014; Baker et al., 2016; Kaviani et al., 2020; Berger et al., 2022). We extend this literature by showing that corporate investment responds not only to firms' direct exposure to trade uncertainty, but also to their indirect exposure through their lenders. Firms borrowing from banks with greater trade-uncertainty exposure experience relatively slower debt growth, investment, and asset growth than other firms. This amplification mechanism underscores how banks' portfolio composition shapes the real effects of uncertainty.

We also contribute to the literature that shows that banks which facilitate international trade amplify the effects of realized balance sheet shocks on firms and households (Amiti and Weinstein, 2011; Niepmann, 2015; Michalski and Ors, 2012; Niepmann and Schmidt-Eisenlohr, 2017; Paravisini et al., 2023). In contrast to this work, we focus on (i) the directional effect from trade to banks and (ii) the role of trade uncertainty, both of which have received comparatively less attention. Federico et al. (2025) show that China's accession to the WTO in 2001 and the resulting increase in import competition raised non-performing loans in Italian banks, generating a balance sheet shock that reallocated credit away from directly affected firms. Hankins et al. (2026) show that the 2018 U.S. steel and aluminum tariffs reduced consumer credit supply through captive auto finance companies. While we share with these studies a focus on trade-related credit effects, we emphasize uncertainty surrounding trade policy rather than the policy itself (for which we directly control). Importantly, we find no evidence of balance sheet deterioration among more exposed banks, yet their loan supply contracts as uncertainty rises. This distinction isolates an uncertainty-driven contraction in credit supply, operating even in the absence of realized balance sheet losses.

Finally, our work builds on a growing literature on the economic consequences of trade tensions and tariff policy, particularly in the context of U.S.-China trade relations. A large body of evidence documents the real effects of the 2018–2019 tariffs and associated trade uncertainty (Handley and Limao, 2017; Caldara et al., 2020; Novy and Taylor, 2020; Fajgelbaum et al., 2024), including adverse impacts on consumption (Waugh, 2020), investment (Amiti et al., 2020), and employment (Flaaen and Pierce, 2024). We show that the economic impact of trade policy extends beyond these direct effects. Trade uncertainty leads to adjustments in banks' lending and portfolio allocation decisions that have independent real consequences for non-financial firms. In doing so, the banking sector can amplify—or potentially dampen—the real effects of the policy itself.

The remainder of the paper proceeds as follows. Section 2 presents a stylized model of bank lending under uncertainty and derives testable implications. Section 3 describes the data. Section 4 presents the main results, and Section 5 provides robustness checks. Section 6 concludes.

2 Stylized Model of Bank Lending under Uncertainty

This section provides a stylized framework to motivate our empirical approach. The key insight, which we highlight here and model formally in Appendix A, is that a change in trade uncertainty can affect bank lending by changing the variance of loan returns for a subset of borrowers operating in sectors with greater exposure to trade uncertainty. In the model, this change in return dispersion affects banks' optimal lending decisions even in the absence of any changes in mean returns. We map the results of the model to hypotheses, which we can then take to the data described in Section 3. Finally, we discuss the implications of uncertainty-induced changes in credit supply for firms (i.e., the "real effects"). This analysis lies outside our stylized model of bank lending under trade uncertainty, so we draw on previous literature to motivate hypotheses.

We focus on banks' lending decisions in the face of uncertainty while operating under financial constraints. Following the work that examines how *aggregate* uncertainty impacts lending (Buch et al., 2015; Valencia, 2017), we provide a stylized model of bank lending to firms in different sectors, whereby these firms are subjected to *sector-specific* shocks rather than aggregate ones. In particular, one set of borrowers is located in a sector subject to an increase in trade uncertainty, which is modeled as an increase in the volatility of their underlying returns (i.e., an increase in the volatility of a subset of borrowers that are more exposed to trade uncertainty).

Banks are risk-neutral and face VaR constraints, which creates a discontinuity in banks' profits from lending.[5] This constraint leads banks to decrease lending when uncertainty increases. In particular, the model (detailed in Appendix A) shows that the VaR constraint becomes tighter as the volatility of loan returns increases, and banks pull back lending to sectors more exposed to trade uncertainty, but not necessarily to less-exposed borrowers. However, even if banks can shift credit toward less-exposed borrowers, total lending may still fall. Importantly, the correlation of shocks across high- and low-exposed sectors determines the extent of this aggregate loan supply response. Because the correlation structure is unobserved, the overall supply-side effect of trade uncertainty on bank lending remains an empirical question—one that our regressions will inform. These mechanisms are exclusively on credit supply, as the framework does not introduce corresponding shifts

[5]Alternatively, we could impose a capital constraint determined by a regulator. Banks facing capital constraints may face external finance premia (Bernanke, 2007).

in the demand for loans by firms.

The model's main results for the bank's supply of loans can be summarized by the following three propositions (see Appendix A for proofs):

> Proposition 1. An increase in trade uncertainty will lead to a contraction in a bank's aggregate lending as long as the correlation of shocks to the high- and low-uncertainty sectors' returns is not too negative.
>
> Proposition 2. An increase in trade uncertainty will lead to a greater contraction in lending by banks more exposed to the high-uncertainty sector, provided that the diversification benefits from cross-sector correlation do not dominate the direct exposure effect.
>
> Proposition 3. An increase in trade uncertainty will lead to a larger contraction in lending by banks with smaller capital buffers in response to higher trade uncertainty.

The model's propositions naturally map to implications that can be tested in our empirical work. Overall, banks that are relatively more exposed to trade uncertainty exhibit behavior consistent with lending under a financial constraint, such as the model's VaR constraint. This is stated formally in the following hypothesis:

Hypothesis 1. *A rise in trade uncertainty leads banks with loan portfolios more exposed to trade uncertainty to reduce credit supply more than banks that are less exposed to the increase in trade uncertainty.*

We next examine additional sources of heterogeneity in bank lending behavior. Proposition 3 shows that the magnitude of adjustments in credit supply after uncertainty shocks depends on banks' capital constraints. Intuitively, capital buffers provide a cushion against the VaR constraint, allowing banks to maintain lending even when their loan portfolio's volatility increases. Concretely, we examine the evidence for this channel as follows:

Hypothesis 2. *A rise in trade uncertainty induces lower-capital banks to contract lending by more than higher-capital banks, conditional on banks' exposures to trade uncertainty.*

Hypotheses 1 and 2 form the basis of our empirical analysis. Moreover, a corollary to Hypothesis 1 is that, conditional on bank balance sheet size remaining unchanged, a larger portion of bank balance sheets will be allocated to assets that are not loans.

Real effects of uncertainty-induced credit supply changes. Having established a set of hypotheses for banks' lending behavior given an increase in trade uncertainty, we next examine how an uncertainty-induced change in credit supply affects borrowing firms. These potential real effects lie outside our stylized bank-lending model, so we rely on previous literature to motivate our hypotheses. Specifically, a contraction in bank lending supply is especially relevant for borrower outcomes when credit market frictions limit firms' ability to substitute their debt financing across banks or to other sources of funds. An extensive literature documents the close link between banks' financial health and the performance of their borrowers (see, e.g., Chava and Purnanandam, 2011; Chodorow-Reich, 2014; Schwert, 2018). Accordingly, we examine evidence for the following:

Hypothesis 3. *Real outcomes are worse for firms that borrow from banks with higher exposures to trade uncertainty relative to firms that borrow from less exposed banks.*

3 Data and Bank Exposure to Trade Uncertainty

Our main data set is the U.S. credit register, described below. Table OA.1 provides definitions and data sources used to construct the variables for the empirical analysis. This section describes the data and our approach to constructing a measure of bank exposure to trade uncertainty.

3.1 The U.S. Credit Register

Our empirical tests leverage microdata from a credit register—the FR Y-14Q H1 Wholesale credit schedule (Y-14 in short). These data are collected quarterly from U.S. and foreign Bank Holding Companies (henceforth 'banks') as part of annual stress tests. Reporting banks have assets above \$50 billion during our sample period. As a result, the Y-14 data set covers the near universe of commercial and industrial (C&I) loans from large stress-tested banks, which account for roughly 70% of total C&I lending (Caglio et al., 2024). The reporting panel comprises 40 banks during 2016–2019, of which 29 banks are in the main regression sample. Quarterly bank financials come from the Consolidated Financial Statements for Holding Companies form FR Y-9C.

The Y-14 data set contains loan-level information on C&I loans of minimum size $1 million to domestic borrowers. We exclude loans to non-financial firms in the utilities and public administration sectors. We use information on the value of loans outstanding and other characteristics of the loans, such as loan pricing (e.g., spreads for floating-rate loans), time to maturity, whether the loan is secured by collateral, loan type (e.g., line of credit or term loan), and collateral type. For each loan, banks report their own estimates of the probability of default over a one-year horizon, computed in line with the Basel II guidelines using internal risk ratings models that are evaluated by bank supervisors. In addition, banks report annual borrower financials such as total assets, fixed assets, cash holdings, tangible assets, sales revenue, and profitability. Unlike other data sets, the Y-14 offers extensive coverage of both public and privately held firms, with borrowers accounting for 64% of non-financial business debt liabilities and 80% of U.S. output (Caglio et al., 2024).

Descriptive statistics for the loans, banks, and firms in our main regression sample are reported in Table 1. The loans in our sample have a median value of $15.6 million and a spread of 175 bps (typically over the prime bank rate or LIBOR). Median loan growth across bank-firm pairs, computed relative to the start of the sample period (2016:Q1), is 0%. Close to 35% of firms belong to high-uncertainty sectors and almost 23% in tariff-hit sectors. We also report additional summary statistics for variables used in complementary tests in Table OA.2. Median remaining time to maturity is 3 years and 12.2% of outstanding loans are new loans (originations and renewals). Furthermore, 64% of loans are revolving credit lines.

3.2 Bank Exposure to Trade Uncertainty

A critical ingredient of our analysis is the measure of bank exposure to trade uncertainty. Construction of this variable proceeds in three steps. First, we use text-based measures of firm-level trade uncertainty for U.S. firms from Hassan et al. (2019) that we average at the 3-digit NAICS industry level. Second, we assign these uncertainty measures to borrowers in the credit register based on their NAICS-3 industry classification. Third, we aggregate this information at the bank level using banks' initial loan shares to individual firms.

Text-based measure of trade uncertainty. Hassan et al. (2019) leverage computational linguistics tools to construct measures of firm risk and uncertainty, specifically using text analysis to obtain the frequency of terms concerning trade uncertainty in quarterly earnings conference call transcripts. The authors calculate the share of earnings calls language that identifies risks associated with specific topics, normalized by text length. Key for our analysis is the topic of *trade risk and uncertainty*, which captures discussions related to international trade and potential risk and uncertainty jointly (e.g., the words "tariffs" and "uncertain" occurring in a call).[6]

Period of rising trade uncertainty. Figure 1 shows the evolution of aggregate trade uncertainty, calculated as the average of firm-level uncertainty between 2014 and 2019. As seen in panel A, trade uncertainty spikes in 2018 and remains elevated in 2019. Moreover, trade uncertainty rises considerably more than other sectoral risks such as those classified as environmental or economic. Caldara et al. (2020) use media- and earnings-calls text-based measures to construct a similar trade uncertainty measure focused on policies. Their index, shown in panel B, depicts a sharp increase in trade policy uncertainty during 2018–2019, which the authors attribute to firms' concerns about supply chain disruptions and higher costs of raw materials caused by the new tariffs. They argue that the more moderate rise in trade uncertainty in 2017 was driven by changes in corporate tax policy, notably the 2017 border tax adjustment proposal. Combined with the fact that tariff hikes on imported goods from the United States' major trading partners started in February 2018 and paused in December 2019 with the U.S.-China Phase One deal, we settle on the 2018–2019 period as reflecting high trade uncertainty for the analysis.[7]

Firm-level indicators of trade uncertainty are available only for listed firms in the Hassan et al. (2019) data set, while the Y-14 credit register covers both public and private firms. Therefore, we obtain sector-level measures of average uncertainty to merge into the credit register and assign to private firms. Average uncertainty for each NAICS-3 industry is the average of firm-level uncer-

[6] The top bigrams for trade in the training library used by the authors include trade agreement, barriers, free trade, markets, trade relations, duties, globalization, labor standards, and policy objectives. Bigrams for risk and uncertainty include risk/risks, uncertainty, variable, change, possibility, uncertain/uncertainty, doubt, prospect, variability, exposed, probability, unknown, unpredictable, and speculative, among others.

[7] Benguria et al. (2022) and Grossman et al. (2024), among others, argue that the 2018–2019 cycle of retaliatory trade actions dramatically increased uncertainty in trade-oriented sectors by reversing decades of trade liberalization. In addition, our choice of trade tensions period is corroborated by the findings of Hassan et al. (2024), who use text analysis of earnings calls for firms worldwide to identify marked increases in perceived country risk. Their analysis identifies a spike in country risk for China during the U.S.-China trade tensions between 2018:Q4 and 2019:Q4. Furthermore, given that trade uncertainty starts rising in 2017, we check that our headline results are robust when we drop data for the year 2017 from the analysis and compare lending outcomes in 2015–2016 versus 2018–2019.

tainty across listed firms in that sector.[8] For the imputation of average uncertainty from listed firms to all firms, we rely on recent evidence that listed firms' equity valuations strongly predict economic activity at the sector level, especially for manufacturing sectors (Flynn and Ghent, 2022), which are over-represented in banks' loan portfolios. We then calculate the change in average trade uncertainty by sector between 2016–2017 and 2018–2019, with these two-year windows serving as pre/post periods in our empirical analysis.

Trade uncertainty across sectors. Table OA.3 reports the change in trade uncertainty for the sectors with the highest increase and decrease in trade uncertainty. It shows that firms in the manufacturing and transportation sectors account for a larger fraction of those that are most affected. However, sectors sort differently on exposure to uncertainty versus tariffs, with only 5 of 14 sectors in the high-uncertainty group actually receiving tariffs. The weak correlation between uncertainty and tariffs is also illustrated in Figure OA.1, which shows that the distributions of changes in uncertainty across sectors with or without tariffs largely overlap.

The second step to construct a measure of bank exposure to trade uncertainty involves merging sector-level trade uncertainty measures with banks' initial loan exposures. The initial loan share is computed relative to total loans and is the average over 2014–2015. This approach helps construct a measure of bank exposure that precedes the 2016–2019 sample period, that is arguably unrelated to economic conditions during that period, and avoids relying on a single year of data which may result in a noisy measure. The measure of bank exposure to trade uncertainty for bank b is defined as a loan share-weighted sum of changes in uncertainty of all sectors that bank b lends to, as:

$$Bank\ Exposure_b^{Trade\ Uncertainty} = \sum_s \omega_{bs,\text{2014-15}} \times \Delta Trade\ Uncertainty_{s,\text{2018-19/2016-17}},$$

where the term $\omega_{bs,2014\text{–}15}$ captures the share of the sum of loans to firms in sector s in bank b's loan portfolio and $\Delta Trade\ Uncertainty_{s,2018\text{–}19/2016\text{–}17}$ measures the change in trade uncertainty for sector s between 2016–2017 and 2018–2019. The average and median bank loan exposures to trade uncertainty are positive, which means that the average bank has a loan portfolio that is tilted

[8] For this aggregation we use industry classifications from S&P Compustat for the firms. We aggregate the firm-level uncertainty information at the NAICS-3 level and not a more granular level to have sufficient firms in each sector for the average to be reliable. We also check that our results are robust to accounting for the sparse firm-level data in some sectors with a weighted least squares estimation in Appendix OA.1.

towards sectors facing higher trade uncertainty during 2018–2019 (Table 1).

Covariate balance by bank exposure. Our empirical analysis employs a DID framework to compare lending outcomes for banks with varying exposure to trade uncertainty. The identifying assumption is that banks do not sort into sectors based on characteristics that simultaneously affect credit supply and exposure to trade uncertainty (Borusyak et al., 2022). To assess this assumption, Table 2 reports a covariate balance test that compares banks with higher and lower exposure (above/below the median and 75th percentile) along a range of observable characteristics, including total assets and asset growth, capital ratio (common equity/assets), core deposit share (core deposits/assets), specialization (a dummy for outsized sectoral exposures as in Paravisini et al., 2020), commercial loan and securities-to-asset ratios, and loan exposure to tariff-hit sectors. Columns 1 and 2 present mean values of these characteristics for each group and column 3 reports p-values for two-sided tests of differences in means across groups. The test indicates that banks are broadly similar across the bank characteristics considered, supporting the identifying assumption. To mitigate potential confounding effects, we include these variables as controls in our specifications.

4 Main Results

This section presents the empirical specifications and results corresponding to the hypotheses developed above. We first assess whether trade uncertainty affects the supply of bank credit to non-financial firms (Section 4.1). Then we test for heterogeneity in bank responses to trade uncertainty depending on capital constraints (Section 4.2) and examine how banks reallocate their assets. Lastly, we present evidence of real effects for borrowing firms (Section 4.3).

4.1 Bank trade uncertainty exposure and credit supply: Hypothesis 1

We start by assessing whether banks adjust their lending activities consistent with potentially binding lending-capacity constraints. According to Hypothesis 1, an increase in bank exposure to trade uncertainty is associated with a reduction in the supply of bank credit. We test this hypothesis with a DID specification linking trade uncertainty to bank lending outcomes:

$$\begin{aligned} y_{b,i,t} = {} & \beta_1 \, Bank\ Exposure_b^{Trade\ Uncertainty} \times Post_t + \beta_2 \, Bank\ Exposure_b^{Tariffs} \times Post_t \\ & + \beta_3 X_{b,t} + \beta_4 X_{b,t} \times Post_t + \gamma_{i,t} + \delta_{b,i} + e_{b,i,t}. \end{aligned} \tag{1}$$

where the dependent variable $y_{b,i,t}$ in the baseline regressions is loan growth (the growth of outstanding loan commitments from bank b to firm i relative to the beginning of the sample period) or the loan spread. The sample includes all loans outstanding between 2016:Q1 and 2019:Q4. We define $Post_t$ as an indicator variable equal to one during 2018:Q1 through 2019:Q4, and zero during 2016:Q1 through 2017:Q4. The variable $Bank\ Exposure_b^{Trade\ Uncertainty}$ is our measure of bank exposure to trade uncertainty as defined in Section 3.2 and the main DID term of interest. A negative value for the β_1 coefficient in the loan growth specification (and a positive one in the loan spread specification) would provide evidence supporting Hypothesis 1.

Specification (1) includes firm×quarter fixed effects ($\gamma_{i,t}$), which implies that β_1 is estimated based on differences in the lending behavior of banks with varying degrees of exposure to uncertainty vis-à-vis a given firm in a given quarter. We also include firm×bank fixed effects ($\delta_{b,i}$) to allow for the possibility that loan demand is specific to the bank-firm pair because of endogenous matching (Chodorow-Reich, 2014; Schwert, 2018). This may be the case when banks specialize in certain types of credit or borrowers (see, e.g., Blickle et al., 2023; Paravisini et al., 2023). To further address the issue of specialization as a possible confounding factor, we control for a bank specialization measure that identifies banks with outsized exposures to individual sectors following the approach in Paravisini et al. (2020). We test the robustness of our results to alternative measures in Section 5.

A crucial control variable is $Bank\ Exposure_b^{Tariffs}$, the bank's loan portfolio exposure to tariff-hit sectors, measured as the 2014–2015 average share of loan commitments to firms in tariff-hit sectors. This variable captures the effect on bank credit supply of changes in expected loan returns related to the actual imposition of tariffs (the first-moment effect). Specification (1) also contains standard determinants of bank lending ($X_{b,t}$), such as size (log-total assets), capital (common equity divided by total assets), and the share of core deposits in total assets. In Section 5 we explore the sensitivity of our specifications to additional controls and finer fixed effects.

Coefficients are estimated with Ordinary Least Squares (OLS) and standard errors are double clustered at the bank and firm level to account for treatment variation at the bank level and for residual serial correlation within firms (Abadie et al., 2023). We examine the robustness of our results to alternative approaches to clustering standard errors at the end of this section.

Baseline results. Table 3 reports estimates for loan growth and spreads based on specification (1). Columns 1-2 present results from a specification using bank, firm, and quarter fixed effects (that do not control for time-varying credit demand shocks), while columns 3-4 add interacted fixed effects (that control for such shocks at the firm level). The point estimates for the DID coefficient of interest, 'Bank exposure to trade uncertainty×Post', are stable across the sets of fixed effects and statistically significant at least at the 10% level. Estimates show that an increase in trade uncertainty is associated with (i) a relative contraction in loan growth and (ii) a relative rise in loan spreads for banks that are more exposed to trade uncertainty. The similarity of estimates across specifications suggests that loan demand does not shift significantly at banks or firms that are more exposed to trade uncertainty. Using the coefficients from columns 3-4, an increase in bank exposure to trade uncertainty by one SD (0.24) is associated with an average decline in loan growth of 6.7 ppts (relative to the median growth rate of loan commitments of 0% over the sample period), and an average increase in loan spreads of 8.1 bps.[9] Loan quantities and prices respond in opposite directions to higher exposure to uncertainty, suggesting a relative reduction in loan supply at more exposed banks, consistent with Hypothesis 1.

Firm risk. One possible reason for the credit contraction at more exposed banks is that their borrowers become riskier. To capture firm risk, we use the forward-looking probability of default (PD) assessed by the bank for each borrower. Y-14 banks calculate PDs following Basel II guidelines and credit risk models evaluated by supervisors. Regressions in Table 4 estimate the effect of banks' exposure to trade uncertainty on their assessment of firm risk, both for the sample of multi-bank firms in the main regression sample (column 1) and for an expanded sample that adds single-lender firms (column 2), which account for 83% of Y-14 firms. Coefficient estimates are statistically

[9] The estimated DID coefficient on banks' exposures to tariff-hit sectors is positive and significant for loan growth and insignificant for loan spreads, indicating that banks more exposed to tariff-hit sectors are willing to supply more credit, consistent with the findings of Alfaro et al. (2025). Coefficient estimates for all bank controls in the baseline specification are reported in Table OA.4.

significant and show that more exposed banks tend to assess their borrowers as relatively riskier during 2018–2019, but the economic magnitude is modest (0.14 ppts change for a one standard deviation increase in bank exposure to trade uncertainty, or about 6% of the sample mean).

Parallel trends. A key identifying assumption behind the unbiased estimation of β_1 is that banks made similar lending decisions before the 2018–2019 period irrespective of their exposure to sectors affected by trade uncertainty. We test the validity of this assumption by exploring the dynamic DID effects in our baseline regressions and a placebo test that shifts the sample period back by several years. Figure 2 plots the individual coefficients for the interaction term between the bank exposure measure and quarterly dummies over the sample period and their confidence intervals. The coefficients on the DID term are statistically insignificant in the three years before the trade war, suggesting a lack of anticipation effects and pre-shock lending adjustment by banks. In contrast, we observe a strong relative contraction in loan growth (panel A) and a rise in spreads (panel B) during 2018–2019.[10] The placebo test checks for patterns similar to our baseline results in the years preceding the sample period to determine if bank exposure to uncertainty captures the effects of unobservable bank characteristics. As shown in panel A of Table OA.5, when we compare lending outcomes during 2013–2014 versus 2015–2016, we find no relation between bank exposure to trade uncertainty and loan growth. The relation with loan spreads is negative, the opposite of the baseline tightening effect that we find. These results reduce potential concerns that our main results capture the effects of unobservables rather than those of exposure to trade uncertainty itself.

Additional loan terms. Next, we assess the effects of bank exposure to uncertainty on additional margins of adjustment: loan maturities and collateral requirements (intensive margin) and the probability of granting new loans (extensive margin). In Table OA.6 we use the same baseline specifications as in Equation (1), but the dependent variables are (a) loan remaining maturity; (b) a dummy variable for loans secured by collateral; and (c) a dummy variable for new loan originations.[11] Panels A and B present specifications with and without interacted firm×quarter

[10] We check for evidence that banks may have anticipated the trade war and started adjusting their lending exposures in the pre-period by dropping loan observations from 2017 and running the regressions on the remaining sample: that is, we compare lending outcomes during 2016 versus 2018–2019. The estimates are reported in panel B of Table OA.5 and show that the baseline results remain unchanged, suggesting a lack of anticipation effects.

[11] In columns 1-2 we follow Li et al. (2023) and include additional loan characteristics as controls (log of loan commitment, dummy variables for floating rate loans), and secured dummy (column 1) or loan maturity (column 2).

fixed effects. Across specifications, the estimates for the main DID coefficient are statistically significant and show that more exposed banks are relatively more likely to shorten loan maturity and tighten collateral requirements, and less likely to grant new loans. Overall, these results provide evidence in support of Hypothesis 1 and suggest that more exposed banks respond to uncertainty by tightening loan supply along multiple margins.

Robustness checks. We subject our main results in columns 3-4 of Table 3 to a battery of robustness checks, discussed in detail in Appendix OA.1. First, while our specifications flexibly allow for time-varying changes in firm unobservables (including risk) with firm×quarter fixed effects, our results are also invariant to controlling for firm risk explicitly with lender-assessed probability of default (Table OA.7). Second, the main findings hold up when restricting the sample to new loans and modified loans (panels A-B of Table OA.8), despite a significant reduction in sample size. Third, the baseline results hold in the sample of single-lender firms (panel C of Table OA.8) and are robust to dropping firm-quarter observations with a single syndicated loan that lacks variation in loan spreads across banks (panel D of Table OA.8). Fourth, our results are robust to alternative approaches to clustering the standard errors, including single clustering on bank and triple clustering on bank, firm, and quarter (Table OA.9).

4.2 The impact of bank-level capital constraints: Hypothesis 2

To examine how the differential effects of trade uncertainty on lending behavior relate to bank capital constraints, we use a modified version of specification (1):

$$\begin{aligned} y_{b,i,t} = & \sum_{\tau=1,2} \beta_\tau Bank\ Exposure_b^{Trade\ Uncertainty} \times Post_t \times Bank\ Type_{b,\tau} \\ & + \beta_3 Bank\ Exposure_b^{Tariffs} \times Post_t + \beta_4 X_{b,t} + \beta_5 X_{b,t} \times Post_t + \gamma_{i,t} + \delta_{b,i} + e_{b,i,t}, \end{aligned} \tag{2}$$

where $\tau = 1$ indicates a *Lower-Capital Bank*, $\tau = 2$ indicates a *Higher-Capital Bank*, and higher-capital banks are those with a capital ratio above the median of the yearly cross-sectional distribution. Evidence of capital constraints supporting Hypothesis 2 would be present if $\beta_1 > \beta_2$.

Results. Table 5 presents the results for the capital constraints channel. Consistent with Hypothesis 2, regression results indicate that lower-capital banks reduce loan growth and increase loan spreads more than higher-capital banks. Estimates show that higher-capital banks do not reduce loan growth significantly, whereas lower-capital banks do (column 1). By contrast, exposed banks with lower capital buffers increase loan spreads almost twice as much as banks with higher capital buffers (column 2). P-values of one-sided t-tests of coefficient equality across bank types indicate that the credit contraction is significantly stronger for more constrained banks.

Portfolio re-balancing. Banks' portfolio rebalancing to other asset classes could provide additional insights in the role of bank capital constraints. If exposed banks anticipate capital constraints to become more binding, they may change allocations from risky commercial loans to safer securities, shrink their balance sheets, or a combination of strategies. To explore this possibility, we examine exposed banks' changes in total assets and broad balance sheet components in bank-level data. In Table 6, panel A examines asset portfolio reallocations for the average bank and panel B allows for heterogeneous effects by level of capital buffers. Regression results indicate that bank exposure to trade uncertainty does not affect bank balance sheet growth (panel A, column 1). However, commercial loans as a percentage of total assets fall (column 2), consistent with the results for commercial loans in the Y-14 data, and the share of securities in total assets at more exposed banks increases (column 3), driven by a rise in government-backed securities (column 4). All these effects are significantly stronger for lower-capital banks (Panel B). In addition, there is no evidence that more exposed banks reallocate capital from commercial loans to other types of loans, such as residential real estate or consumer loans, nor to cash, including reserves (Table OA.10).

4.3 Real effects for firms: Hypothesis 3

Hypothesis 3 posits that the credit supply impact of trade uncertainty affects firms' real outcomes. To test this hypothesis, we construct a measure of firm exposure to trade uncertainty through the firm's relationships with its lenders and relate this measure to firm outcomes. Firm exposure to trade uncertainty (through banks) is a continuous variable representing the average uncertainty exposure of a firm's lenders, weighted by the share of each lender in the total firm's borrowing (at the end of 2014), and is defined as:

$$Firm\ Exposure_i^{Trade\ Uncertainty} = \sum_b \omega_{ib,2014} \times Bank\ Exposure_b^{Trade\ Uncertainty}, \tag{3}$$

where $\omega_{ib,2014}$ is firm i's beginning-of-sample loan share from each bank b, and $Bank\ Exposure_b^{Trade\ Uncertainty}$ is bank b's exposure to trade uncertainty.

Covariate balance by firm exposure. We test for selection on observables by comparing firms with exposure to uncertainty above versus below the median or 75th percentile of the cross-sectional distribution. Table OA.11 reports differences between the two groups across key firm characteristics, including size (log-assets), leverage (debt/assets), liquidity (cash/assets), profitability, investment rate, and speculative-grade status. A scale-invariant test of equality of group means (Imbens and Rubin, 2015) shows that covariates are balanced across exposure groups. The only exception is a firm's presence in tariff-affected sectors, which is positively correlated with firms' exposure to uncertainty through banks and for which we carefully control for in the empirical analysis.

Next, we use the following specification to test for real effects over the period 2016–2019:

$$\begin{aligned} y_{i,s,c,t} = {} & \beta_1 Firm\ Exposure_i^{Trade\ Uncertainty} \times Post_t + \beta_2 Firm\ Exposure_i^{Tariffs} \times Post_t \\ & + \beta_3 X_{i,t} + \beta_4 X_{i,t} \times Post_t + \gamma_i + \delta_{s,c,t} + e_{i,s,c,t}, \end{aligned} \tag{4}$$

and $y_{i,s,c,t}$ refers to total debt growth, bank debt growth (growth rate of total outstanding Y-14 bank loans), the investment rate (growth rate of fixed assets divided by lagged total assets), or total asset growth for firm i in sector s, located in county c and in year t. All dependent variables are yearly except bank debt growth, which is computed from the Y-14 quarterly data. A key control variable is the firm's exposure to tariffs through the firm's relationships with its lenders ($Firm\ Exposure_i^{Tariffs}$), which is computed in the same way as firm exposure to uncertainty through the firm's lenders. We also control for firm characteristics and risk attributes ($X_{i,t}$), including firm size, leverage, liquidity, asset tangibility (share of tangible assets), return on assets, a dummy variable for firms with a speculative-grade rating, and real sales growth, a proxy for the product demand and growth opportunities facing firms (Whited and Wu, 2006).

Specifications include firm fixed effects (γ_i) and sector×county×year fixed effects ($\delta_{s,c,t}$) to absorb shocks affecting all firms in a given (3-digit NAICS) industry and county over time. Importantly, the sector×year effects (spanned by sector×county×year fixed effects) control for firms' direct exposure to trade uncertainty at the sector level and help isolate the effect of firms' *indirect* exposure to uncertainty through their lenders. A negative and statistically significant β_1 coefficient would provide support for Hypothesis 3. In addition to testing for the effect of trade uncertainty on firm outcomes, we break down the DID term of interest ($Firm\ Exposure_i^{Trade\ Uncertainty} \times Post_t$) by a measure of bank dependence, namely a dummy variable that takes a value of one for firms with an above-average share of bank debt (approximated with the sum of loans from Y-14 banks). We anticipate larger real effects for more bank-dependent firms to the extent that such firms are less able to secure financing in public debt markets than other firms. In these regressions, coefficients are estimated with OLS and standard errors are clustered at the firm level.

Results. Estimation results are presented in Table 7. Panel A estimates on the DID coefficient of interest are statistically significant at the 1% level and show that higher firm exposure to trade uncertainty is associated with relatively slower growth in firms' total debt, bank debt, and lower investment rates (columns 1-3). These findings suggest that firms in borrowing relationships with more exposed banks are unable to fully substitute reduced credit from more exposed banks with other sources of financing and provide empirical support for Hypothesis 3. The relative contraction in investment, in turn, has a significant effect on firms' ability to grow their assets (column 4). The coefficient estimates in column 3 indicate that a one SD increase in firm exposure to trade uncertainty is associated with a reduction in the investment rate by 4.1 ppts, representing close to one-tenth of a SD of the investment rate.

In panel B of Table 7, we test whether bank-dependent firms are relatively more adversely affected. Across specifications, estimates reveal significantly larger effects of uncertainty on total and bank debt growth, asset growth, and investment rates for firms with higher bank dependence. P-values for one-sided t-tests of coefficient equality across firm types consistently reject the null hypothesis of equal effects in favor of larger effects for more bank-dependent firms. Taken together, these findings highlight that firms borrowing from exposed banks experience worse economic outcomes as trade uncertainty rises, which suggests that they cannot costlessly switch to alternative sources of finance.

Direct versus indirect uncertainty. Table 8 examines whether the effects of firm exposure to uncertainty through its lenders—our indirect channel—are distinct from and operate above and beyond firms' own direct exposure to trade uncertainty.[12] For this purpose, we run "horse race" specifications that simultaneously include our baseline indirect measure and a measure of firms' direct exposure: the average trade uncertainty across public firms in the firm's NAICS-3 industry from Hassan et al. (2019).[13] Estimates in column 1 confirm the baseline finding that higher uncertainty is negatively and significantly associated with firm investment. Column 2 adds firms' direct exposure to uncertainty: the coefficient on the indirect channel remains negative and statistically significant, while the coefficient on direct uncertainty is insignificant. This result establishes that the bank-exposure to trade uncertainty channel has economically meaningful effects on firm investment above and beyond firms' direct exposure to uncertainty.

In columns 3–4 of Table 8, we interact both the indirect and direct uncertainty measures with a dummy variable for firms in tariff-hit sectors. This exercise allows us to determine if the effects of uncertainty on firm investment are confined to firms in tariff-hit sectors or apply more generally outside of that sector. Estimates in column 4 have two main takeaways. First, indirect uncertainty reduces investment broadly across sectors irrespective of tariff exposure: the coefficient on the indirect measure is negative and significant, with no incremental effect for firms in tariff-hit sectors. This result suggests that the indirect channel operates broadly across the loan portfolio to transmit the effects of trade uncertainty beyond tariff-hit sectors. Second, the direct effect of uncertainty on investment is concentrated in tariff-hit sectors. Taken together, these findings show that the direct and indirect channels operate simultaneously, confirming that the bank-exposure channel is distinct from and economically meaningful beyond the direct effects of uncertainty on firm investment.

[12]There is a well-established economics literature that studies the real effects of uncertainty. Early influential theoretical contributions include Bernanke (1983); Pindyck (1991); Caballero and Pindyck (1992), and Dixit and Pindyck (1994). Empirical studies that establish a negative relationship between uncertainty and investment, as firms tend to postpone investment until uncertainty subsides, include Bloom et al. (2007); Bloom (2009), and Handley and Limao (2015).

[13]Since the level effect of a sector-level measure cannot be estimated if we include sector×county×year fixed effects, we replace those fixed effects with county×year fixed effects.

Parallel trends. We test the validity of the parallel trends assumption for the real-effects regressions in the dynamic DID coefficient charts in Figure OA.2, which plots the individual coefficients for the interaction term between the firm exposure measure and yearly dummies over 2014–2019 and their confidence intervals. Across all outcomes considered—debt growth, investment rate, and asset growth—coefficients on the DID term are statistically insignificant in the four years before the trade tensions, supporting the assumption of parallel pre-trends in the outcomes of exposed firms. In contrast, exposed firms' outcomes deteriorate significantly in the 2018–2019 period.

Robustness checks. We subject our real-effects results to two robustness checks. First, we check for substitution across lenders at a more aggregated level. Estimation results in Table OA.12 show that our firm-level real effects largely hold up when we aggregate the data from firm level to sector-county level. Second, we replace the 3-digit industry classification with a finer industry classification in order to better absorb unobserved demand and other sectoral shocks. Estimates in Table OA.13 show that our baseline results are robust to using 4-digit and 6-digit NAICS classifications, with all main DID coefficients retaining the expected signs and statistical significance.

5 Ruling Out Alternative Explanations and Additional Results

It is important to establish that our results are not driven by concurrent changes in credit demand, increased loan delinquencies on bank balance sheets, or changes in macroeconomic conditions during 2018–2019. Here, we entertain several alternative explanations for our results and offer evidence suggesting that our findings are not driven by these explanations. In addition, we briefly describe a battery of additional robustness checks (with details in Appendix OA.1).

Credit demand. Our baseline analysis shows that banks with higher exposure to trade uncertainty have lower loan commitment growth and higher spreads on loans to borrowing firms, consistent with a contraction in credit availability. To bolster our evidence that this credit contraction reflects supply rather than demand forces, we present two additional results. First, we check how the main DID coefficient varies across high versus low-uncertainty borrowing firms. This comparison is informative because high-uncertainty firms would arguably experience a greater change in demand than low-uncertainty firms, biasing our coefficients if demand effects confounded our results. Yet, the estimates in Table OA.14 show that the relative credit contraction of more exposed banks is quantitatively similar by firm exposure to uncertainty (the coefficients for low- and high-uncertainty sectors are not different from each other).

Second, we leverage our Y-14 data on loan utilizations, which refer to the amount of utilized credit for revolvers and the full amount of credit for term loans, and are less likely to be contaminated by supply-side decisions than loan commitments. Using these data, we examine if loan utilization growth changed differentially at more affected banks and firms. We also examine changes in credit line utilization rates, which are informative about shifts in credit demand because revolver limits are pre-committed and banks cannot prevent drawdowns unless covenants are breached (Greenwald et al., 2024). Results in columns 1-2 of Table OA.15 show no relation between bank exposure to trade uncertainty and utilized loan growth in our main loan-level sample. Furthermore, estimates in columns 3-4 show that firms in higher-uncertainty sectors exhibit similar drawdown rates in 2018–2019 as other firms.[14] Overall, the results suggest that the relative reduction in loan commitments at more affected banks—our baseline result—reflects supply-side lending decisions rather than a shift in credit demand from borrowers.

Loan losses and bank balance sheet shock. Our baseline analysis suggests that more exposed banks' relative credit contraction is driven by expectations of a wider distribution of loan returns (as opposed to lower average returns). A potential concern may be that this contraction is confounded by a balance sheet shock in the form of higher expected or realized loan delinquencies. In Table OA.16 we use bank balance sheet data to determine if banks with higher exposure to uncertainty experience differential changes in asset quality. The dependent variables are the ratio of loan loss reserves (a forward-looking measure of loan performance), non-performing loans, and net charge-offs to total gross loans. The DID coefficient estimates are insignificant across outcome variables, indicating no evidence that higher loan losses or a bank balance sheet shock are driving our results.

Controlling for bank specialization. Another confounding factor may stem from specialized banks' business models, a pervasive feature of commercial banking. Banks with industry expertise

[14] In contrast, firms in tariff-hit sectors have higher utilization rates than in other sectors, suggesting increased demand for liquidity to manage higher trade costs, consistent with the findings (Alfaro et al., 2025).

might find it optimal to provide additional support to affected firms during stress, leveraging their information advantage and the value of long-term relationships (Boot et al., 1993; Petersen and Rajan, 1995; Giannetti and Saidi, 2018). We conduct additional tests to determine if the specialized banks in our sample provide additional support to their borrowers during times of heightened uncertainty. Our specifications control for bank specialization defined as in Paravisini et al. (2020) as a dummy variable for bank-sector pairs where the bank has an outsized lending exposure to a particular sector (see Table OA.4). In panels A and B of Table OA.17, we control for bank specialization using additional measures from Paravisini et al. (2023) and Blickle et al. (2023), which capture lending specialization in trade-oriented firms engaged in trade activities with Asia—a region at the forefront of the 2018–2019 trade tensions—or industry specialization relative to a market-based benchmark, respectively. Estimates on the 'Specialization×Post' coefficient in these specifications show that bank specialization does not significantly predict lending outcomes during 2018–2019, providing no evidence that banks' specialized knowledge plays a stabilizing role during periods of trade uncertainty.

Controlling for non-tariff trade policy measures. Tariffs were the dominant instrument of U.S. trade policies during the 2018–2019 period, directly affecting approximately 15% of listed firms at the peak of the trade tensions (Clayton et al., 2025). Other policy actions such as sanctions and export controls had more confined effects because they were narrowly targeted to particular firms, sectors, or countries. To ensure our results are not driven by banks' exposures to foreign markets that experienced sanctions or to U.S. borrowers hit by retaliatory tariffs, we conduct two additional tests. First, we check that our results hold up when controlling for banks' commercial lending exposure to countries sanctioned by the United States during 2016–2019, measured as the average share of loans to foreign borrowers in sanctioned countries in total bank assets over this period. Second, we drop from the sample exporting firms subject to retaliatory tariffs, whose real outcomes may have been directly impacted by those tariffs. Estimates in panels A-B of Table OA.18 show that our main results are insensitive to these changes.

Controlling for concurrent macroeconomic developments. Two additional tests assuage concerns that our results may be driven by bank exposures to the protracted 2014-2015 oil price decline or by fluctuations in exchange rates over the sample period. The sharp and sustained oil price decline that started in mid-2014 led banks with higher exposures to the oil sector to contract lending, especially to oil firms (Bidder et al., 2021). To make sure our results do not pick up these developments, we drop oil companies from the regression sample (broadly identified as those in the "Mining, quarrying, and oil and gas extraction" NAICS-2 sector). As seen in panel C of Table OA.18, this sample change does not alter the results.

We also explore whether our results are driven by exchange rate fluctuations, which may co-move with trade uncertainty, given that the value of the U.S. dollar affects both bank asset quality and trade activities. Exchange rate fluctuations affect banks and firms through several mechanisms. When the dollar appreciates, banks may pull back from lending if they expect the repayment capacity of their unhedged foreign borrowers to deteriorate. A stronger dollar also reduces the purchasing power of foreign firms, which can make it harder for some U.S. firms to sell their goods abroad, impairing their ability to generate revenues. In addition, a stronger dollar is associated with tighter dollar credit conditions (Niepmann and Schmidt-Eisenlohr, 2023; Bruno and Shin, 2023), which implies that foreign exporters more reliant on dollar-funded bank credit may experience a decline in credit access (Meisenzahl et al., 2021) and a slowdown in real activity. In turn, the growth prospects of U.S. firms that rely on imported intermediate inputs could suffer. We address the possibility that fluctuations in the value of the U.S. dollar may affect our results by including in our main regressions as an additional control: the interaction of bank loan exposure to firms in tradable-goods producing sectors (arguably more affected by U.S. dollar fluctuations than firms in other sectors) with the U.S. dollar broad exchange rate index. As seen in panel D of Table OA.18, the statistical and economic significance of our main DID coefficients remain virtually the same.

Additional robustness checks. Appendix OA.1 provides detailed descriptions of additional robustness exercises. We assess the sensitivity of our results along several dimensions. First, we include finer firm×loan-purpose×time fixed effects to account for potential bank specialization (panels C and D of Table OA.17). Second, we control for banks' exposure to non-trade uncertainty and for the cyclicality of their lending portfolios (panels A and B of Table OA.19). Third, we incorporate collateral-type×year fixed effects (panel C of Table OA.19) to account for the possibility that credit dynamics following financial shocks can vary significantly across these loan types. Finally, we employ an alternative estimator and construct a "leave-one-sector-out" measure of banks' exposure to trade uncertainty (Table OA.20). Across all specifications, our baseline results remain robust.

6 Conclusion

This paper shows that trade uncertainty has adverse effects on U.S. banks' supply of credit to non-financial firms. Exploiting the large and sustained increase in trade uncertainty during 2018–2019, together with comprehensive loan-level data for U.S. banks and firms, we document that banks with greater exposure to sectors experiencing larger increases in trade uncertainty contract lending, with negative real effects for bank-dependent firms. The findings are consistent with banks facing potentially binding lending-capacity constraints becoming more cautious in deploying capital to risky commercial lending and reallocating portfolios toward safer securities.

Our results highlight an important banking channel in the transmission of uncertainty to the real economy, showing that bank exposure to uncertainty shapes the magnitude of real effects above and beyond firms' direct exposure to uncertainty. A full accounting of the economic consequences of trade disputes should therefore incorporate the endogenous responses of the financial sector. Understanding how financial intermediaries propagate real-sector uncertainty shocks—particularly those originating in international trade policy—remains an important direction for future research.

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A Theoretical Framework

This appendix provides a simple theoretical framework that analyzes under what conditions banks will reduce loan supply when trade uncertainty rises. The model extends the work of Buch, Buchholz and Tonzer (2015), who model a competitive banking sector that faces aggregate risk. Our extension allows banks to lend to multiple sectors of the economy and for banks to have different exposure in their lending to these sectors. We treat bank exposure differences as exogenous, which maps to our empirical setup where banks' exposure to trade uncertainty is pre-determined.[15] To simplify the notation and be consistent with our empirical setup, we assume that there are only two sectors (or types of firms) in the economy, with sectors that are identical except that they are subject to High and Low trade uncertainty. We show how banks change their lending behavior when the uncertainty of H sector's returns increases.

A.1 Bank problem

Consider the balance sheet of bank i. Total assets at time t, ta_{it}, are composed of a portfolio of loans l_{it} plus cash and liquid assets, denoted by c_{it}. The liabilities' side is composed of deposits d_{it} and equity e_{it}. The portfolio of loans pays an uncertain return at $t+1$, denoted by r_{it+1}, which has a positive expected return at t, denoted by $E_t[r_{it+1}] > 0$.

Given this notation, the bank's equity in $t+1$ can be expressed as

$$\begin{aligned} e_{it+1} &= (1 + r_{it+1})l_{it} + c_{it} - d_{it} \\ &= e_{it} + r_{it+1}l_{it}. \end{aligned} \tag{A.5}$$

A bank defaults in period $t+1$ if its equity is negative. That is, if $e_{it+1} = e_{it} + r_{it+1}l_{it} < 0$, or in terms of the loan portfolio's rate of return:

$$r_{it+1} < -\frac{e_{it}}{l_{it}}. \tag{A.6}$$

Value at risk constraint. Assume that banks are risk neutral but have the following Value-at-Risk (VaR) constraint:

$$Prob\left(r_{it+1} < -\frac{e_{it}}{l_{it}}\right) \leq 1 - \alpha, \tag{A.7}$$

[15] The model is static, but follows in the same spirit of a more dynamic setup such as Valencia (2017).

which states that a bank's VaR loss is defined as the loss not to be exceeded with probability $1-\alpha$; i.e., $\text{VaR}_\alpha = \frac{e_{it}}{l_{it}}$.[16] This VaR constraint is a convenient way to reflect how banks manage their risk. The VaR constraint can also be defined as a deviation from the mean measured in terms of its standard deviation:

$$Prob\left(r_{it+1} < \mu_i - \phi_i \sigma_{it}\right) \leq 1-\alpha, \tag{A.8}$$

where μ_i is the (constant) mean return that is assumed to be greater than zero; σ_{it} is time-varying return volatility, which is assumed to be known at time t and captures uncertainty in the model, and ϕ_i is a constant that can be interpreted as a bank's capital buffer—a bank will remain solvent as long as $r_{it} > \mu - \phi_i \sigma_{it}$.

Bank i's problem is to maximize e_{it+1} at $t+1$. If the bank did not face a VaR constraint it would lend as much as possible given that the expected return on lending is positive. However, the VaR constraint puts a cap on the total amount of lending as in Buch, Buchholz and Tonzer (2015). This can be seen by combining (A.7) and (A.8) to arrive at:

$$l_{it} = \frac{e_{it}}{\phi_i \sigma_{it} - \mu_i}. \tag{A.9}$$

Banks' loan portfolios. The framework has been silent on the composition of a bank's i loan portfolio, l_{it}. We build on the prior literature by assuming that a bank can lend to borrowers that operate in sectors that are exposed to different degrees of trade uncertainty. We denote these two sectors as High and Low trade uncertainty sectors. Total loans, l_{it} can therefore be written as:

$$l_{it} = l_{it}^H + l_{it}^L,$$

where l_{it}^s denotes loans made to sector $s = \{H, L\}$. It is convenient to also define the share of loans to each sector as $\omega_{it}^s \equiv \frac{l_{it}^s}{l_{it}}$ with $\omega_{it}^H + \omega_{it}^L = 1$.

We can then write the loan portfolio's return at $t+1$ as a function of a bank i's lending to the two sectors as

$$r_{it+1} = \omega_{it}^H r_{it+1}^H + \omega_{it}^L r_{it+1}^L, \tag{A.10}$$

which is simply the weighted average of returns to lending to each sector conditional on time t loan shares, which we take as exogenously given—that is, we do not model the bank's allocation of lending across sectors, which parallels our empirical strategy that treats banks' lending exposure to trade uncertainty as pre-determined.

[16] For example, regulators would intervene if this constraint is hit.

A.2 Modeling uncertainty faced by banks

We assume that the rate of return from bank i's lending to sector i follows the stochastic process, where returns in each sector are subject to time-varying volatility:

$$r^s_{it+1} = \mu^s_i + \sigma^s_t \varepsilon^s_{it+1} \tag{A.11}$$

for $s = H, L$. Shocks to loan returns are i.i.d. over time, $\varepsilon^s_{it} \sim N(0, 1)$, but may be correlated *contemporaneously*: $\rho \equiv corr(\varepsilon^H_{it}, \varepsilon^L_{it}) \gtreqless 0$. Furthermore, we assume that firms in the H sector become exposed to greater return volatility, $\sigma^H_t > \sigma^L_t$, which captures the notion of an additional source of risk arising from trade uncertainty.

Using equations (A.10) and (A.11), we can express the mean of the loan portfolio for bank i, μ_i, as a function of the corresponding moments at the sector level:

$$\begin{aligned} E[r_{it+1}] &= \omega^H_{it} E[r^H_{it+1}] + \omega^L_{it} E[r^L_{it+1}] \\ &= \omega^H_{it} E[\mu^H_i + \sigma^H_t \varepsilon^H_{it+1}] + \omega^L_{it} E[\mu^L_i + \sigma^L_t \varepsilon^L_{it+1}] \\ &= \omega^H_{it} \mu^H_i + \omega^L_{it} \mu^L_i. \end{aligned} \tag{A.12}$$

Similarly, the time-varying volatility of loan portfolio returns for bank i, σ^2_{it}, can be solved for as:

$$\begin{aligned} Var[r_{it+1}] &= Var[\omega^H_{it} r^H_{it+1} + \omega^L_{it} r^L_{it+1}] \\ &= (\omega^H_{it} \sigma^H_t)^2 + (\omega^L_{it} \sigma^L_t)^2 + 2\omega^H_{it} \omega^L_{it} \rho \sigma^H_t \sigma^L_t. \end{aligned} \tag{A.13}$$

Using equations (A.12) and (A.13), we can write the loan portfolio's return, r_{it+1}, as the following stochastic process:

$$r_{it+1} = \mu_i + \sigma_{it} \varepsilon_{it+1}, \tag{A.14}$$

where $\varepsilon_{it+1} \equiv \omega^H_{it} \varepsilon^H_{it+1} + \omega^L_{it} \varepsilon^L_{it+1}$ is i.i.d. over time.

A.3 Banks' lending reaction to a change in trade uncertainty

Given the above setup, consider how bank lending reacts to an increase in trade uncertainty—i.e., an increase in σ^H_t. The first result of this analysis is summarized by the following proposition:

Proposition 1 *An increase in trade uncertainty will lead to a contraction in bank i lending as long as the correlation of shocks to H and L sectors' returns is not too negative. Specifically, if we* *measure the impact of trade uncertainty on lending as* $\frac{\partial\left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H}$, *the following inequality holds:*

$$\frac{\partial\left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H} < 0 \quad \textit{if } \rho > -\frac{\omega_{it}^H \sigma_t^H}{\omega_{it}^L \sigma_t^L}.$$

Proof: First, using equations (A.5), (A.9), and (A.14) it is straightforward to show that the change in total loans relative to lagged total assets is

$$\frac{\Delta l_{it}}{ta_{it-1}} = \frac{\frac{e_{it-1}}{ta_{it-1}}\left(1 + \frac{r_{it}}{\phi_i \sigma_{it-1} - \mu_i}\right)}{(\phi_i \sigma_{it} - \mu_i)} - \frac{\frac{e_{it-1}}{ta_{it-1}}}{\phi_i \sigma_{it-1} - \mu_i}. \tag{A.15}$$

We are interested in studying $\partial\left(\frac{\Delta l_{it}}{ta_{it-1}}\right)/\partial \sigma_t^H$. Therefore, taking the partial derivative of (A.15) and using the definition of the variance of the aggregate bank-level return in equation (A.13), yields:

$$\frac{\partial\left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H} = -\frac{e_{it-1}}{ta_{it-1}} \cdot \frac{\left(1 + \frac{r_{it}}{\phi_i \sigma_{it-1} - \mu_i}\right)\phi_i \omega_{it}^H}{\sigma_{it}(\phi_i \sigma_{it} - \mu_i)^2}\left[\omega_{it}^H \sigma_t^H + \omega_{it}^L \rho \sigma_t^L\right] \tag{A.16}$$

which is negative if $\rho > -\frac{\omega_t^H \sigma_t^H}{\omega_t^L \sigma_t^L}$ and positive otherwise. ■

Therefore, the change in bank lending in reaction to an increase in trade uncertainty will be negative so long as shocks to low- and high-uncertainty sectors are not too negatively correlated. However, the theory cannot rule out an alternative outcome: if this correlation is strongly negative, banks could expand their overall lending in the face of increased trade volatility. In this case, it is worthwhile for banks to shift lending to borrowers in L-type sectors from borrowers in H-type sectors such that the increase in lending to L-types dominates the decrease in lending to H-types.

A.4 Bank-level heterogeneity

Bank exposure to trade uncertainty. The result in Proposition 1 holds for all banks, regardless of a bank's lending exposure to trade uncertainty—that is for a given share of loans to the H sector, ω_{it}^H. Our baseline regression specification leverages the difference in the exposure for identification. We extend Proposition 1 to map the model to our baseline regression in the following proposition:

Proposition 2 *An increase in trade uncertainty will lead to a greater contraction in lending for banks more exposed to the H sector, provided that the diversification benefits from cross-sector* *correlation do not dominate the direct exposure effect. Specifically, the following inequality holds:*

$$\frac{\partial^2 \left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H \partial \omega_{it}^H} < 0 \quad \textit{if} \quad \Gamma_i > 0,$$

where $\Gamma_i \equiv 2\omega_{it}^H \sigma_t^H + (\omega_{it}^L - \omega_{it}^H)\rho\sigma_t^L > 0$.

This condition is satisfied when:

1. $\rho \geq 0$ *(non-negative correlation), or*
2. $\rho < 0$ *but* $|\rho| < \frac{2\omega_{it}^H \sigma_t^H}{(\omega_{it}^H - \omega_{it}^L)\sigma_t^L}$ *when* $\omega_{it}^H > \omega_{it}^L$*, or*
3. $\omega_{it}^L \geq \omega_{it}^H$ *and* $\rho > -\frac{2\omega_{it}^H \sigma_t^H}{(\omega_{it}^L - \omega_{it}^H)\sigma_t^L}$.

Proof: The result follows from taking a further derivative of (A.16):

$$\frac{\partial^2 \left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H \partial \omega_{it}^H} = -\frac{e_{it-1}}{ta_{it-1}} \cdot \frac{\left(1 + \frac{r_{it}}{\phi_i \sigma_{it-1} - \mu_i}\right)\phi_i}{\sigma_{it}(\phi_i \sigma_{it} - \mu_i)^2} \left[2\omega_{it}^H \sigma_t^H + (\omega_{it}^L - \omega_{it}^H)\rho\sigma_t^L\right], \tag{A.17}$$

which is negative if $2\omega_{it}^H \sigma_t^H + (\omega_{it}^L - \omega_{it}^H)\rho\sigma_t^L > 0$. Note that this derivation ignores the change in return volatility arising from changes in loan shares; i.e., $\partial\sigma_{it}/\partial\omega_{it}^H$. This simplification coincides with the cross-sectional variation in bank exposure to trade uncertainty that we exploit in our empirical setup being pre-determined. ■

Bank capital. We further explore how bank heterogeneity impacts bank lending in the face of increased trade uncertainty by exploring the role of bank capital. This allows us to explore how the variation in capital across banks interacts with the cross-section of banks' exposure to trade uncertainty when this uncertainty rises. In particular, the following proposition holds:

Proposition 3 *Banks with smaller capital buffers exhibit a larger differential lending response to trade uncertainty based on their H-sector exposure. Formally:*

$$\frac{\partial^3 \left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H \partial \omega_{it}^H \partial \phi_i} > 0 \quad \textit{if} \quad \Gamma_{it} > 0,$$

where $\Gamma_{it} \equiv 2\omega_{it}^H \sigma_t^H + (\omega_{it}^L - \omega_{it}^H)\rho\sigma_t^L$ *captures the net risk sensitivity of H-sector exposure, accounting for both:*

- *the direct amplification of portfolio risk from H-sector lending, and*

- *the indirect diversification effect through cross-sector correlation.*

Intuitively, large capital buffers provide a cushion against the VaR constraint, allowing banks to maintain lending even when portfolio volatility increases. This cushion is more valuable for banks whose exposure to the H-sector amplifies their sensitivity to trade uncertainty (i.e., when $\Gamma_{it} > 0$*).*

Proof: From equation (A.17):

$$\frac{\partial^2 \left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H \partial \omega_{it}^H} = -\frac{\alpha}{\sigma_{it}} \cdot g(\phi_i) \cdot \Gamma_{it},$$

where $g(\phi_i) \equiv \frac{\phi_i}{(\phi_i \sigma_{it} - \mu_i)^2}$; $\alpha \equiv \frac{e_{it-1}}{ta_{it-1}} \left(1 + \frac{r_{it}}{\phi_i \sigma_{it-1} - \mu_i}\right) > 0$; $\Gamma_{it} \equiv 2\omega_{it}^H \sigma_t^H + (\omega_{it}^L - \omega_{it}^H)\rho\sigma_t^L$.

Differentiating $g(\phi_i)$ with respect to ϕ_i:

$$\frac{\partial g}{\partial \phi_i} = -\frac{\phi_i \sigma_{it} + \mu_i}{(\phi_i \sigma_{it} - \mu_i)^3} < 0$$

Therefore:

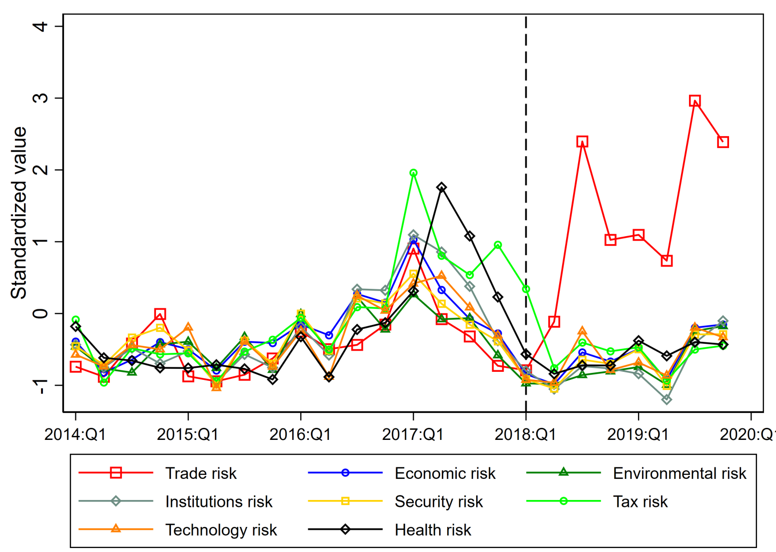
$$\frac{\partial^3 \left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H \partial \omega_{it}^H \partial \phi_i} = \frac{e_{it-1}}{ta_{it-1}} \cdot \frac{\left(1 + \frac{r_{it}}{\phi_i \sigma_{it-1} - \mu_i}\right)(\phi_i \sigma_{it} + \mu_i)}{\sigma_{it}(\phi_i \sigma_{it} - \mu_i)^3} \cdot \Gamma_{it}. \tag{A.18}$$

Since all leading terms are positive for solvent banks, the sign depends only on Γ_{it}: $\frac{\partial^3 \left(\frac{\Delta l_{it}}{ta_{it-1}}\right)}{\partial \sigma_t^H \partial \omega_{it}^H \partial \phi_i} > 0 \quad \text{if} \quad \Gamma_{it} > 0$. ∎

Figure 1. Trade and other uncertainty indices

This figure depicts the evolution of the trade uncertainty index compared to other indices of sectoral risk from Hassan et al. (2019) (Panel A) and the trade policy uncertainty index from Caldara et al. (2020) (Panel B). All indexes are based on text analysis of quarterly earnings call transcripts of listed firms and represent the frequency of terms concerning trade risk and uncertainty capturing discussions related to international trade and potential risks and uncertainty jointly (scaled by total text length). The Caldara et al. (2020) index focuses on the intensity of discussions related to the policy component of trade uncertainty. Time-series for all indexes are obtained from firm-level data by taking the average across firms and are standardized. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources.

A. Trade uncertainty vs. sectoral uncertainty



B. Trade uncertainty vs. trade policy uncertainty

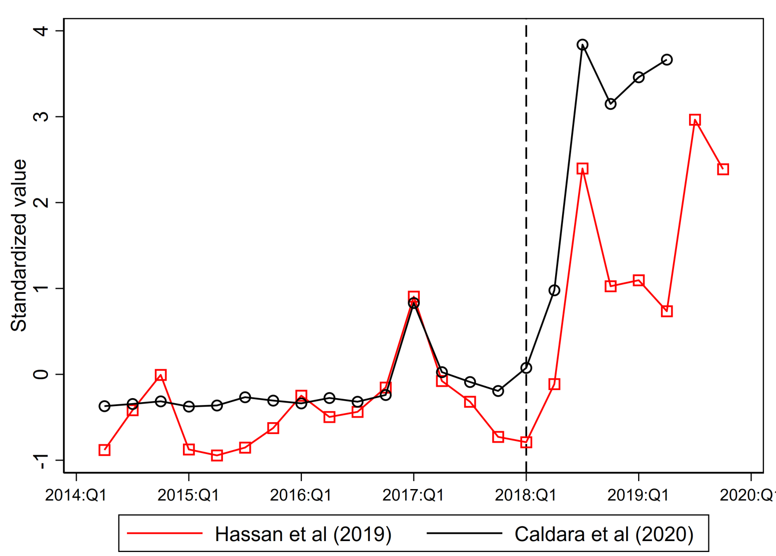
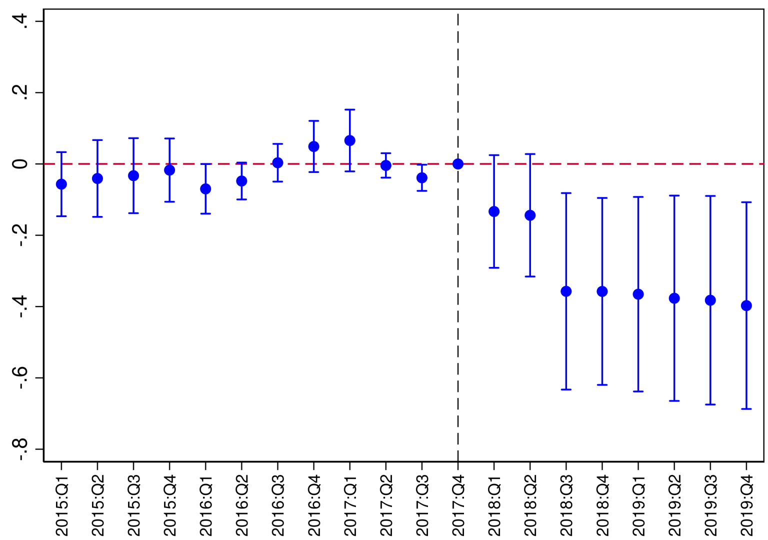


Figure 2. Dynamic DID coefficient chart for main lending outcomes

This figure shows the estimated marginal effects of bank exposure to trade uncertainty on loan growth (panel A) and loan spreads (panel B) during 2015:Q1–2019:Q4. The charts plot the estimated DID coefficients and the associated 90% confidence intervals of the dynamic variant of the specifications in columns 3 (loan growth) and column 4 (for spreads) in Table 3 with interaction effects between bank exposure and quarterly dummies. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources.

A. Loan growth



B. Loan spreads

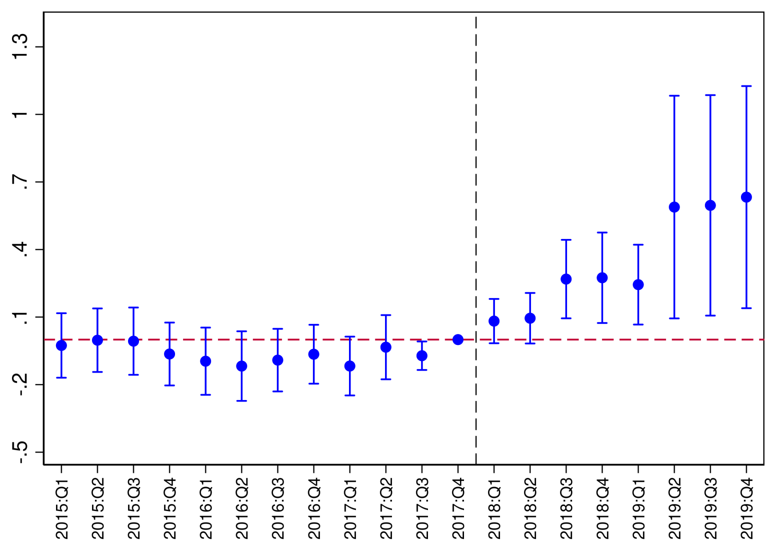


Table 1. Main descriptive statistics

This table reports selected summary statistics at the bank level (panel A), loan level (panel B), and firm level (panel C), respectively. The loan-level regression sample refers to U.S. banks with at least $50 billion in assets that participate in Dodd-Frank stress tests and report to the FR Y-14 before the end of 2019. The regressions sample includes loans to domestic non-financial firms, excluding utilities and public administration sectors. In panel C, all variables are yearly except bank debt growth, which is computed from the credit register and is quarterly. Values for all growth rates are reported in decimals. See Section 3 for data descriptions, Section 3.2 for details on the construction of bank exposure to trade uncertainty and tariff measures, and Table OA.1 for variable definitions and sources.

	N	Mean	St. Dev.	P25	P50	P75
(A) Bank-level data						
Bank exposure to trade uncertainty	457	1.791	0.241	1.650	1.810	1.890
Bank exposure to tariff-hit sectors	457	0.330	0.099	0.270	0.324	0.381
Total assets (USD bn)	457	528.2	703.6	131.0	211.6	409.0
Capital ratio (common equity/assets)	457	0.114	0.019	0.101	0.114	0.129
Core deposits/Assets	457	0.643	0.167	0.561	0.699	0.760
Bank specialization (Paravisini et al., 2020)	457	0.140	0.099	0.096	0.107	0.134
Total asset growth	455	0.037	0.067	0.006	0.029	0.050
Commercial loans/Assets	457	0.256	0.139	0.155	0.256	0.347
Securities/Assets	457	0.247	0.083	0.177	0.229	0.320
Government securities/Assets	457	0.147	0.051	0.114	0.150	0.178
(B) Loan-level data						
Loan amount (USD million)	683999	35.193	80.616	4.225	15.636	41.786
Loan growth (commitments)	683999	-0.250	1.013	-0.624	0.000	0.303
Loan spread (ppts)	382426	1.983	1.201	1.250	1.750	2.512
Probability of default	645091	0.024	0.090	0.002	0.006	0.015
(C) Firm-level data						
Firm exposure to trade uncertainty	67664	1.575	0.515	1.521	1.820	1.872
Firm exposure to tariff-hit sectors	67664	0.277	0.100	0.227	0.292	0.339
Firm sectoral uncertainty	67459	0.149	0.351	-0.052	0.109	0.287
Firm in high-uncertainty sector	67459	0.346	0.476	0.000	0.000	1.000
Firm in tariff-hit sector	67664	0.226	0.418	0.000	0.000	0.000
Firm total debt growth	67664	0.043	0.441	-0.139	0.008	0.211
Firm investment rate	66722	0.059	0.410	-0.076	0.006	0.135
Firm total asset growth	67603	0.060	0.255	-0.028	0.038	0.129
Firm bank debt growth	227406	0.300	1.703	-0.250	-0.018	0.288

Table 2. Covariate balance by bank exposure to trade uncertainty

This table presents a covariate balance test for banks with higher versus lower exposure to trade uncertainty, for the regression sample comprising $N = 29$ banks. Panels A and B report mean characteristics for banks split around the median and the 75th percentile of exposure, respectively. Bank exposure to trade uncertainty is measured as the average of the difference in trade uncertainty across sectors (between 2016–2017 and 2018–2019), weighted by initial bank loans shares to those sectors (See Section 3.2). See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. * indicates significance at the 10% level.

	(1) **High exposure bank**	(2) **Low exposure bank**	(3) **pvalue t-test (1)=(2)**
(A) Around the median of exposure	**N=14**	**N=15**	
Total assets (log)	19.809	19.076	0.060*
Capital ratio (common equity/assets)	0.110	0.119	0.249
Core deposits/assets	0.648	0.647	0.985
Specialization	0.152	0.127	0.515
Exposure to tariff-hit sectors	0.358	0.299	0.116
Asset growth	0.010	0.015	0.738
Commercial loans/Assets	0.220	0.287	0.207
Securities/Assets	0.251	0.239	0.694
Government securities/Assets	0.145	0.150	0.791
(B) Around the 75th percentile of exposure	**N=7**	**N=22**	
Total assets (log)	19.771	19.321	0.335
Capital ratio (common equity/assets)	0.105	0.118	0.150
Core deposits/assets	0.593	0.665	0.344
Specialization	0.144	0.137	0.890
Exposure to tariff-hit sectors	0.372	0.313	0.187
Asset growth	0.020	0.010	0.578
Commercial loans/Assets	0.199	0.272	0.239
Securities/Assets	0.248	0.243	0.893
Government securities/Assets	0.137	0.151	0.533

Table 3. Trade uncertainty and bank lending

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty. The data are at the loan-level and refer to outstanding loans to domestic non-financial firms, observed on a quarterly basis, during the period 2016–2019. Bank exposure to trade uncertainty is measured as the average of the difference in trade uncertainty across sectors (between 2016–2017 and 2018–2019), weighted by initial bank loans shares to those sectors (See Section 3.2). The dummy variable *Post* takes a value of one for the period 2018–2019 and zero for the period 2016–2017. Bank controls include bank exposure to tariff-hit sectors, bank size (log-total assets), capital (common equity/total assets), deposits (core deposits/total assets), and bank specialization, and enter in levels and interacted with *Post*. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**	(3) **Loan growth**	(4) **Loan spread**
Bank exposure to trade uncertainty×Post	-0.285**	0.316*	-0.278**	0.338***
	(0.104)	(0.155)	(0.121)	(0.118)
Bank exposure to tariff-hit sectors×Post	0.514**	0.482	0.514*	0.264
	(0.221)	(0.387)	(0.284)	(0.237)
Observations	683,999	357,187	683,999	357,187
R-squared	0.131	0.664	0.342	0.850
Bank controls×Post	Y	Y	Y	Y
Bank FE	Y	Y	-	-
Firm FE	Y	Y	-	-
Quarter FE	Y	Y	-	-
Firm×Bank FE	-	-	Y	Y
Firm×Quarter FE	-	-	Y	Y

Table 4. Trade uncertainty and firm risk

This table shows OLS estimates for a regression of loan-level probability of default on bank exposure to trade uncertainty. The data are at the loan-level and refer to outstanding loans to domestic non-financial firms, observed on a quarterly basis, during the period 2016–2019. Bank exposure to trade uncertainty is measured as the average of the difference in trade uncertainty across sectors (between 2016–2017 and 2018–2019), weighted by initial bank loans shares to those sectors (See Section 3.2). The dummy variable *Post* takes a value of one for the period 2018–2019 and zero for the period 2016–2017. In panel A, the sample includes multi-bank firms from the baseline Khwaja-Mian sample in Table 3; specifications in panel B expand the sample to also include single-bank firms. Specification and controls are as in baseline Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)
Dependent variable:	**Probability of default**	
	(A) Multi-bank firms	**(B) All firms**
Bank exposure to trade uncertainty×Post	0.0056**	0.0060**
	(0.0022)	(0.0022)
Bank exposure to tariff-hit sectors×Post	-0.0153*	-0.0151**
	(0.0078)	(0.0062)
Observations	728,648	1,667,331
R-squared	0.4943	0.5641
Bank controls×Post	Y	Y
Bank FE	Y	Y
Firm FE	Y	Y
Quarter FE	Y	Y

Table 5. Trade uncertainty, bank lending, and capital constraints

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty that allows heterogeneous effects by bank capital. The measure of capital is common equity divided by total assets and higher-capital banks have above-median capital ratios. The data are at the loan-level and refer to outstanding loans to domestic non-financial firms, observed on a quarterly basis, during the period 2016–2019. Bank exposure to trade uncertainty is measured as the average of the difference in trade uncertainty across sectors (between 2016–2017 and 2018–2019), weighted by initial bank loans shares to those sectors (See Section 3.2). The dummy variable *Post* takes a value of one for the period 2018–2019 and zero for the period 2016–2017. Specification and controls are as in baseline Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**
Bank exposure to trade uncertainty×Post×Lower capital [1]	-0.388**	0.469**
	(0.143)	(0.173)
Bank exposure to trade uncertainty×Post×Higher capital [2]	-0.096	0.232*
	(0.074)	(0.116)
Bank exposure to tariff-hit sectors×Post	0.650**	0.144
	(0.259)	(0.217)
p-value t-test: $H_a : \|1\| > \|2\|$	0.013	0.075
Observations	683,999	357,187
R-squared	0.343	0.850
Bank controls×Post	Y	Y
Firm×Quarter FE	Y	Y
Firm×Bank FE	Y	Y

Table 6. Trade uncertainty and bank reallocation to other assets

This table shows OLS estimates for a regression of bank-level total asset growth, commercial loan-to-asset ratio, securities-to-asset ratio, and government securities-to-asset ratio on bank exposure to uncertainty (panel A) allowing heterogeneous effects by bank capital (panel B). The data are at the bank-quarter level during the period 2016–2019. In panel B, the measure of capital is common equity divided by total assets and higher-capital banks have above-median capital ratios. The dummy variable *Post* takes a value of one for the period 2018–2019 and zero for the period 2016–2017. Specification and controls are as in baseline Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the bank level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Total asset growth**	(2) **Commercial loans (% assets)**	(3) **Securities (% assets)**	(4) **Government securities (% assets)**
		(A) Baseline		
Bank exposure to trade uncertainty×Post	0.041	-0.030***	0.043**	0.025**
	(0.042)	(0.014)	(0.016)	(0.010)
Bank exposure to tariff-hit sectors×Post	0.004	0.041	-0.031	-0.077***
	(0.117)	(0.053)	(0.036)	(0.022)
Observations	455	457	457	457
R-squared	0.440	0.992	0.975	0.956
		(B) By higher and lower bank capital		
Bank exp. to trade unc.×Post×Lower capital [1]	0.022	-0.069***	0.062***	0.030**
	(0.060)	(0.011)	(0.022)	(0.012)
Bank exp. to trade unc.×Post×Higher capital [2]	0.054	0.004	0.027	0.019
	(0.080)	(0.021)	(0.021)	(0.018)
Bank exposure to tariff-hit sectors×Post	0.021	0.057	-0.037	-0.077***
	(0.120)	(0.046)	(0.040)	(0.024)
p-value t-test: $H_a : \|1\| > \|2\|$	-	0.001	-	-
Observations	455	457	457	457
R-squared	0.453	0.993	0.976	0.957
Bank controls×Post	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y

Table 7. Real effects of trade uncertainty through bank lending

This table shows OLS estimates for a regression of firm-level total debt growth, bank debt growth, investment rate, and asset growth on firm exposure to trade uncertainty through its lenders (panel A), allowing for heterogeneous effects by firm's share of bank debt (panel B). The data are at the firm-year level (columns 1, 3, 4) or firm-quarter level (column 2) during the period 2016–2019. The dummy variable *Post* takes a value of one for the period 2018–2019 and zero for the period 2016–2017. Firm exposure to trade uncertainty through its lenders is computed as the average exposure to trade uncertainty of the banks from which a given firm borrows, weighted by relative importance of each bank in the firms' total bank debt (sum of loans from Y-14 banks) at end-2014. Bank debt growth refers to the growth rate of total bank debt defined as the sum of loans from Y-14 banks. Investment rate is the log-difference in fixed capital stock divided by lagged total assets. In panel B, higher bank debt share is defined as above-median average share of bank loans in the firm's total debt during 2016–2017. Firm controls include firm exposure to tariffs-hit sectors through its lenders, firm size (log-assets), leverage, cash holdings, tangibility, return on assets, real sales growth, and a dummy variable taking a value of one for firms rated speculative-grade. Firm sector is 3-digit NAICS classification. Time in the sector×county×time FEs refers to quarter in column 2 and year in remaining columns. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Total debt growth**	(2) **Bank debt growth**	(3) **Investment rate**	(4) **Asset growth**
	(A) Level effect			
Firm exposure to trade uncertainty×Post	-0.058***	-0.184***	-0.080***	-0.058***
	(0.021)	(0.061)	(0.023)	(0.012)
Firm exposure to tariff-hit sectors×Post	0.158	0.227	0.326***	0.200***
	(0.106)	(0.298)	(0.117)	(0.062)
Observations	67,664	227,406	66,518	67,563
R-squared	0.581	0.419	0.550	0.636
	(B) By firms with higher and lower bank debt share			
Firm exp. to trade unc.×Post×Higher bank debt share [1]	-0.070***	-0.248***	-0.086***	-0.064***
	(0.021)	(0.062)	(0.023)	(0.013)
Firm exp. to trade unc.×Post×Lower bank debt share [2]	-0.050**	-0.162***	-0.076***	-0.057***
	(0.021)	(0.061)	(0.023)	(0.013)
Firm exposure to tariff-hit sectors×Post	0.142	0.213	0.318***	0.197***
	(0.107)	(0.297)	(0.118)	(0.063)
p-value t-test: $H_a : \|1\| > \|2\|$	0.000	0.000	0.034	0.013
Observations	66,923	227,406	65,787	66,826
R-squared	0.579	0.419	0.548	0.635
Firm controls×Post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Sector×County×Time FE	Y	Y	Y	Y

Table 8. Real effects of "direct" versus "indirect" trade uncertainty

This table shows OLS estimates for a regression of firm-level investment rate on firm exposure to trade uncertainty through its lenders ("indirect uncertainty") and sector-level uncertainty ("direct uncertainty"). The data are at the firm-year level for the period 2016–2019. The dummy variable *Post* takes a value of one for the period 2018–2019 and zero for the period 2016–2017. Firm exposure to trade uncertainty through its lenders is computed as the average exposure to trade uncertainty of the banks from which a given firm borrows, weighted by relative importance of each bank in the firms' total bank debt (sum of loans from Y-14 banks) at end-2014. Firm's sectoral uncertainty (direct) is the average uncertainty across public firms in a given NAICS-3 industry based on the Hassan et al. (2019) dataset. Firm in tariff-hit sector is a dummy variable taking a value of one for firms in NAICS-4 industries hit by tariffs during 2018–2019. Specification and controls as in Table 7. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the firm level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Investment rate**			
Firm exposure to trade uncertainty×Post	-0.032***	-0.031***	-0.031***	-0.036***
	(0.008)	(0.008)	(0.008)	(0.009)
Firm exposure to trade uncertainty ×Firm in tariff-hit sector×Post				0.019
				(0.011)
Firm sectoral uncertainty ×Post		-0.003	0.007	0.006
		(0.010)	(0.013)	(0.013)
Firm sectoral uncertainty ×Firm in tariff-hit sector×Post			-0.033*	-0.032*
			(0.020)	(0.020)
Observations	66,618	66,416	66,416	66,416
R-squared	0.441	0.442	0.442	0.442
Firm controls×Post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
County×Year FE	Y	Y	Y	Y

ONLINE APPENDIX

Trade Uncertainty and U.S. Bank Lending

Ricardo Correa, Julian di Giovanni, Linda S. Goldberg, Camelia Minoiu

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OA.1 Additional Robustness Checks

This section presents additional tests that validate the identification strategy and examine the robustness of our results to alternative methodological choices. First, we discuss a series of robustness checks of our baseline findings (columns 3-4 in Table 3) in alternative samples of loans. Then, we re-estimate our baseline specifications with finer fixed effects and with additional controls for bank exposure to non-trade uncertainty and a measure of the cyclicality of banks' lending portfolios. We also explore an alternative estimator and a bank exposure to uncertainty measure that is based on a "leave-one-sector-out" approach.

New loans. Our empirical hypotheses are tested on a data set of outstanding loans in the Y-14 data, observed on a quarterly frequency. These tests exploit variation in lending terms that arises from multiple margins: (i) the extension of new loans (such as new loan originations and loans that are renewed upon maturity), which represent 12.2% of outstanding loans; and (ii) ex-post modifications and renegotiations of existing loans (also referred to as loan amendments). Loan renegotiations and modifications are a routine feature of commercial lending contracts, providing substantial flexibility in the terms of existing loans (Roberts and Sufi, 2009). For the Y-14 data, Bidder et al. (2025) show that 42% of loans are modified at least once, with amendments typically involving maturity extensions and interest rate changes.

In panels A-B of Table OA.8, we verify that our results are robust in the sample of new loans. In panel A, the dependent variable is the log of loan commitments because for new originations we cannot calculate a within bank-firm pair loan growth equivalent. Furthermore, we replace the bank×firm fixed effects with bank fixed effects. Despite the significant reduction in sample size, the DID coefficient estimates are similar to our baseline results. In addition, we construct a combined sample of new loan originations and loans subject to significant modifications. Following Bidder et al. (2025), we define modified loans as those loans that exhibit, across two consecutive quarters, a change in interest rate of at least 50 bps and an extension of maturities of at least one quarter. We select a relatively high threshold for interest rate modification to avoid identifying an excessive number of loans as modified and artificially boost our sample size. The results corresponding to this sample of new and modified loans are shown in panel B of Table OA.8, with estimated DID coefficients that are both statistically significant and similar to those in our baseline results.

Single-lender firms. The majority of non-financial firms in the Y-14 data (83%, more precisely) have only one bank relationship and are therefore excluded from our Khwaja-Mian regression sample, raising the question of whether our main findings extend to these firms. Results for single-lender firms are shown in panel C of Table OA.8. In these specifications, we replace the firm×quarter fixed effects with sector×quarter and state×quarter fixed effects. These fixed effects absorb time-varying common shocks to credit demand within narrow groups of similar firms, in the spirit of Degryse et al. (2019). Estimates show that higher bank exposure to trade uncertainty is associated with significantly lower loan growth and higher spreads for this set of firms.

Syndicated loans. Syndicated loans account for 29% of loan observations in our baseline specification and may pose a problem in our Khwaja-Mian sample the extent that interest rate spread, a term that is determined at the deal level (Ivashina, 2005), lacks variation across participating banks. Such cases would reduce the variation in loan spreads and lead to an attenuation bias in our coefficient of interest. To address this issue, we drop all firm-quarter observations where a borrower only has one syndicated loan in that quarter. The sample size declines by less than 6,000 observations, since most firms have either multiple bilateral or syndicated loans, or a combination of such loans. The results in panel D of Table OA.8 show that our main DID coefficient remains statistically significant and almost identical in size to the one obtained in our baseline specification of Table 3 (0.340 vs 0.338).

Controlling for finer fixed effects. If firms have different types of loan relationships across banks (for instance, they take trade finance loans from one bank and other types of loans from another bank), then loan demand could be bank-specific and firm×time fixed effects would fail to absorb all variation in loan demand (Paravisini et al., 2023). To address this issue, we estimate our baseline specifications with finer fixed effects. In panel C of Table OA.17, we consider trade financing loans (letters of credit and loan performance guarantees) versus other loans, which would capture bank specialization in trade finance. In panel D of Table OA.17 we follow Greenwald et al. (2024) and consider a broader set of categories including "Mergers and Acquisition," "Working Capital," "Real estate investment or acquisition," and "All other purposes" as separate loan types. As seen, our main DID coefficient estimates are robust to the inclusion of firm×loan-type×time fixed effects.

In addition, loans collateralized by different types of assets should be considered separately because credit dynamics following monetary and financial shocks can vary significantly across these loan types (Ivashina et al., 2021). Panel C of Table OA.19 shows that our main results do not change when we add loan collateral-type×time fixed effects, where collateral refers to asset-based loans, earnings-based loans, and unsecured loans, using the classification proposed in Caglio et al.

(2024).

Controlling for bank exposure to non-trade uncertainty. Our measures of trade uncertainty may capture risk factors that are unrelated to international trade and shifts in U.S. trade policies, nevertheless co-move with these factors to generate spurious results. Panel A of Figure 1 suggests such a confounding effect is unlikely given the notable jump in trade uncertainty and not in other sectoral risks during 2018–2019. We consider a regression where we control for bank exposure to other sources of uncertainty, at the sector level, that are unrelated to trade. The first measure is computed in the same way as the baseline bank exposure to trade uncertainty, with the only difference that it captures uncertainty from all sectors other than trade, and is obtained by extracting the first principal component from uncertainty indexes for the following sectors: economic policy and budget, environment, institutions and political processes, health care, security and defense, tax policy, and technology and infrastructure. The results of this specification are reported in panel A of Table OA.19 and show that our results remain unchanged when we include this additional control.

Bank cyclicality. Our findings could also be confounded by the bank exposure to trade uncertainty capturing the degree of cyclicality on banks' lending portfolios—i.e., the sensitivity of a bank's lending portfolio to monetary and financial conditions. If this were the case, then the results would reflect a standard bank lending channel of monetary policy rather than the effects of trade uncertainty. To address this possibility, we measure the extent of loan book cyclicality, for each bank in our sample, as the long-run correlation of the growth rate of a banks' total loan commitments and that of the overall banking sector. Our main estimates are robust to controlling for this measure of bank cyclicality in interaction with the *Post* dummy (see panel B of Table OA.19): if anything, bank cyclicality operates in the opposite direction of uncertainty, with more cyclical banks increasing loan volumes more than other banks, and leaving spreads unchanged, during 2018–2019.

Heterogeneous effects for credit lines versus term loans. Do banks tighten credit supply differentially across credit lines (mainly used by firms as a source of liquidity insurance) versus term loans (mainly used for financing investment)? This test allows us to rule out a "credit channel" of dollar movements by which a stronger dollar tightens liquidity conditions in the secondary market for syndicated credits (Niepmann and Schmidt-Eisenlohr, 2023). This channel predicts that our results should be stronger for term loans, which are more likely than credit lines to be sold in the secondary market for syndicated credits (Gatev and Strahan, 2009). When we estimate the baseline DID term separately for credit lines and term loans, we find that credit lines are still affected by an increase in trade uncertainty, although the effects are smaller than those for term loans (panel D of

Table OA.19), with the coefficient for loan spreads large and statistically significant while that for loan growth is insignificant. These results suggest that our baseline findings are not entirely driven by a credit channel of dollar movements.

Alternative estimator—Weighted least squares. Our results may be influenced by sectors for which trade uncertainty is computed with less precision because of the sparse coverage of public firms in the Hassan et al. (2019) data set for which text analysis is performed to measure uncertainty. To account for this issue, we estimate our baseline specifications using weighted-least squares—an estimator that accounts for variations in the precision of sectoral estimates of trade uncertainty. Weights are computed using the bank-specific average firm count of observations used to calculate the trade uncertainty exposure measures. The results in panel A of Table OA.20 show that applying this weighting does not affect our main findings.

"Leave-one-sector-out" construction of bank exposure to trade uncertainty. In panel B of Table OA.20 we report regression results corresponding to a slight modification in the construction of the bank exposure to trade uncertainty measure. Here, we define a continuous "leave-one-sector-out" measure of bank exposure to trade uncertainty, which varies on bank-sector pair $\{b, s\}$, as:

$$Bank\ Exposure^{Uncertainty}_{b,s} = \sum_{s' \neq s} \omega_{bs',\text{2014-15}} \times \Delta Trade\ Uncertainty_{s',\text{2018-19/2016-17}},$$

where s' represents any given sector except sector s. The exposure measure thus leaves out direct information on uncertainty for sector s and instead creates a loan share-weighted sum of changes in uncertainty of all other sectors that bank b lends to, where the term $\omega_{bs',2014\text{–}15}$ captures the share of the sum of loans to firms in sector s' in bank b's loan portfolio and $\Delta Uncertainty_{s',2018\text{–}19/2016\text{–}17}$ measures the change in trade uncertainty for sector s'. This approach for generating the bank-sector exposure measure closely follows the "leave-one-sector-out" approach suggested in Borusyak et al. (2022) and implemented, for instance, in Federico et al. (2025). As seen in panel B of Table OA.20, replacing our main measure with this "leave-one-sector-out" construction leaves our main DID coefficients nearly unchanged. The small difference in results arises because the "leave one out correction" tends to be empirically minor when averaging over sufficiently many observations (e.g., see Goldsmith-Pinkham et al., 2020, in the context of shift-share instruments).

Figure OA.1. Changes in trade uncertainty versus tariffs

The figure depicts overlaid smoothed histograms of NAICS-3 sector-level changes in trade uncertainty between 2016–2017 and 2018–2019 for sectors subject to tariffs and sectors that did not receive tariffs. The unit of measurement for "Change in trade uncertainty" is the frequency of mentions of synonyms for risk or uncertainty, divided by transcript length and multiplied by 1,000. For clarity, change in trade uncertainty is winsorized at the bottom 1% and top 5% of observations. The histograms use the Epanechnikov kernel with optimal bandwidth. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources.

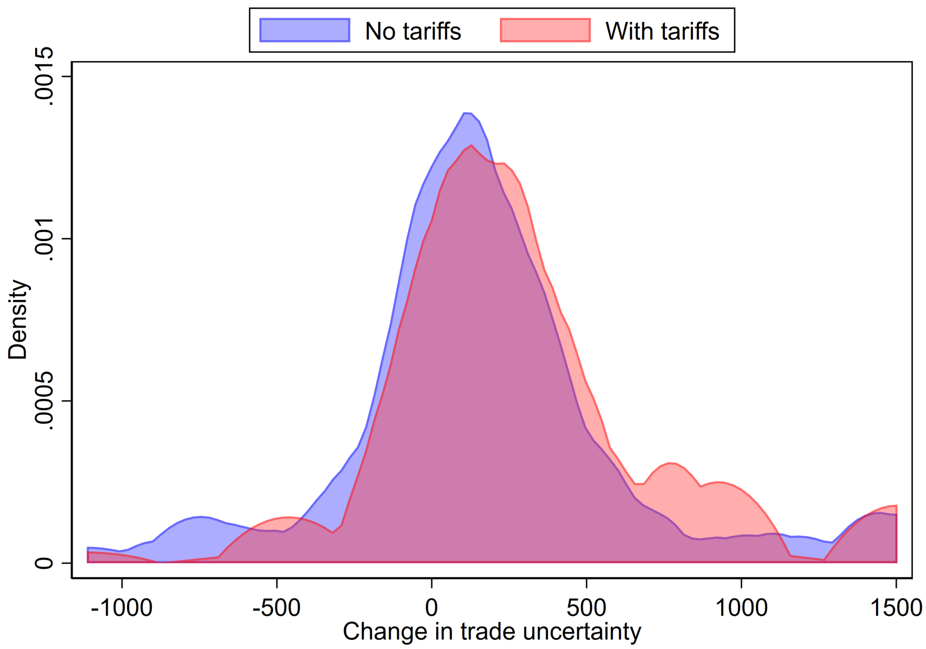
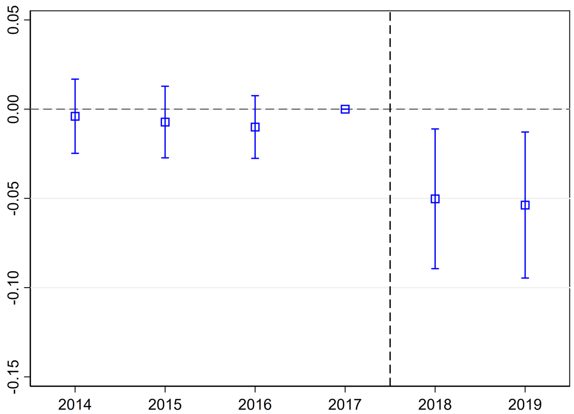


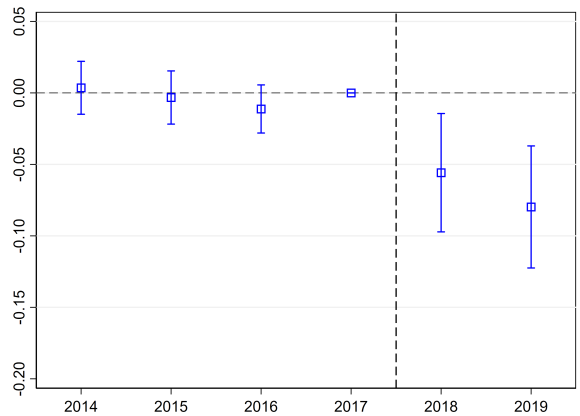
Figure OA.2. Dynamic difference-in-difference coefficients for real-effects regressions

This figure shows the estimated marginal effects of firm exposure to trade uncertainty (via banks) on total debt growth (panel A), investment rate (panel B), and total asset growth (panel C) during 2013–2019. The charts plot the estimated DID coefficients and the associated 95% confidence intervals of the dynamic variant of the specifications in Table 7 with interaction effects between firm exposure to uncertainty and yearly dummies (columns 1, 3, 4). Standard errors are clustered at the firm level. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources.

A. Total debt growth



B. Investment rate



C. Total asset growth

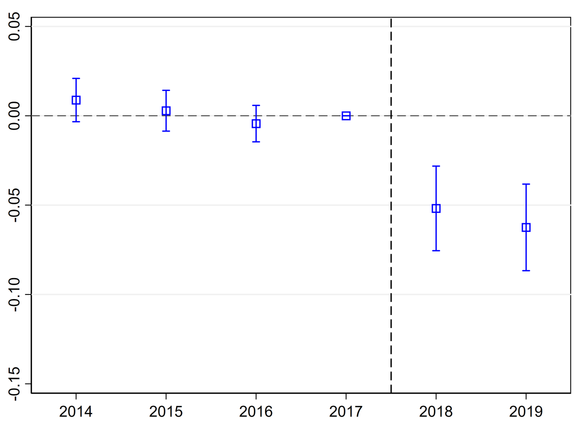


Table OA.1. Variable definitions and sources

Variable	Definition	Source
(A) Bank-level variables		
Bank exposure to trade uncertainty—Baseline measure (See Section 3.2 for details on the construction of this measure.)	The average of the difference in trade uncertainty across NAICS-3 sectors (between 2016-2017 and 2018-2019), weighted by initial bank loans shares to those sectors. Sector-level averages of trade uncertainty are taken across public firms. Trade uncertainty is the frequency of mentions of synonyms for risk or uncertainty, divided by transcript length and multiplied by 1,000.	Authors' calculations using Y-14 and Hassan et al. (2019). Data downloaded from Firm Level Risk.
Bank exposure to tariff-hit sectors	The average share of loan commitments to borrowers in NAICS-4 sectors that received tariffs during 2018–2019, over 2014–2015. We take sectors to be tariff-hit if the new tariff share of costs is positive.	Authors' calculations using Y-14 and Flaaen and Pierce (2024).
Bank specialization (Paravisini et al., 2020)	Dummy variable for banks with outsized loan portfolio exposures to individual NAICS-4 sectors at end-2017. Takes a value of one for bank-sector observations for which the bank's loan share to a given sector exceeds a certain threshold beyond which the exposure is deemed outsized. Threshold is 75th percentile plus 1.5 interquartile ranges of the distribution of loan shares across banks in a given year. Varies on bank-NAICS4 sector level.	Authors' calculation based on Paravisini et al. (2020) (Definition 1, page 13).
Bank specialization (Paravisini et al., 2023)	Dummy variable taking a value of one for those banks with a weighted loan portfolio share to borrowers engaged in trade with firms in countries from the Asia-Pacific region above the 75th percentile, over 2016-2017. Countries in the Asia-Pacific region are based on the IMF World Economic Outlook.	Alfaro et al. (2025)
Bank specialization (Blickle et al., 2023)	Relative specialization in term loans: The ratio of the bank's share of lending to an industry compared with what that industry should get based on overall market shares. Varies on bank-NAICS2 sector level and is averaged over 2016-2017.	Blickle et al. (2023)
Bank exposure to sanctioned countries	Bank loan share to foreign borrowers who are resident in sanctioned countries (directly or through hosted foreign subsidiaries) during 2016-2019. Foreign lending is obtained from the FFIEC 009 form. List of sanctioned countries is sourced from the GSDB.	Authors' calculations using the Global Sanctions Data Base (GSDB) and FR FFIEC 009 form.
Bank loan portfolio cyclicality	Time-invariant measure of the correlation between the bank's C&I loan growth and the growth rate of banking sector assets, obtained by regressing C&I loan growth on banking sector asset growth for each bank in the dataset, over the period 1985:Q1–2021:Q2, using quarterly merger-adjusted Call Report and assigning each Y-14 BHC the main commercial bank from the Call Report.	Authors' calculations using the merger-adjusted Call Report.

Table OA.1. Variable definitions and sources (continued)

Bank exposure to tradable-goods sectors	Bank loan share to tradable-goods sectors, average over 2016-2017. Following Desai et al. (2008), we classify non-tradable sectors to include construction, retailers, transportation, and recreation. (Utilities and financial firms are excluded.)	Authors' calculations using Y-14.
Bank exposure to non-trade uncertainty	Measure of bank exposure to uncertainty computed in the same way as the baseline measure using "non-trade uncertainty."	Authors' calculations using Y-14.
Bank exposure to trade uncertainty (leave-one-sector-out)	Measure of bank exposure to trade uncertainty computed using "take-one-sector-out" approach suggested by Borusyak et al. (2022) and that varies at the bank-NAICS-3 industry level.	Authors' calculations using Y-14.
Bank total asset growth	Yearly log-change in total bank assets.	Authors' calculations using Y-9C.

(B) Loan-level data

Loan growth	Log-difference between the committed amount at time t and that at the start of the sample (2016:Q1) for a given bank-firm pair	Authors' calculations in Y-14
Loan growth (utilization)	Log-difference between the utilized amount at time t and that at the start of the sample (2016:Q1) for a given bank-firm pair	Authors' calculations in Y-14
Loan spread	Interest rate spread over base rate in pps for floating-rate loans.	Y-14
Loan is credit line	Dummy variable for credit lines identified using the credit facility type.	Y-14
Loan is floating rate	Loans flagged as "floating" by the interest rate variability variable.	Y-14
Time to maturity	Remaining time to maturity in the reporting quarter (in years).	Authors' calculations in Y-14
Loan is secured	Dummy variable for collateralized loans with any reported loan collateral (security) type. Takes value 0 for loans flagged by the loan security variable as "unsecured".	Y-14
Probability of default (PD)	Bank's assessment of the default probability associated with each loan facility, according to Basel II guidelines and default models reviewed by supervisors.	Y-14
New loan origination	Dummy variable for newly originated loans.	Y-14
New loan (originations and renewals)	Dummy variable for newly originated loans and loans that are renewed upon maturity.	Y-14
New loan (originations and modifications)	Dummy variable for newly originated loans and loans that are substantially modified over time. Modified loans are identified following Bidder et al. (2025) as those loans experiencing, in any given quarter, a contractual change of at least 50 bps in the loan spread or at least one-quarter in the loan maturity.	Authors' calculations in Y-14

Table OA.1. Variable definitions and sources (continued)

(C) Firm-level variables		
Firm exposure to trade uncertainty	The average exposure to trade uncertainty of the banks from which a given firm borrows, weighted by relative importance of each bank in the firms' total bank debt (sum of loans from Y-14 banks) over 2014-2015.	Authors' calculations using Y-14
Firm exposure to tariff-hit sectors	The average exposure to tariff-hit sectors of the banks from which a given firm borrows, weighted by relative importance of each bank in the firms' total bank debt over 2014-2015.	Authors' calculations using Y-14 and Flaaen and Pierce (2024)
Firm in tariff-hit sector	Dummy variable taking a value of one for the firms in NAICS-4 industries that received tariffs during 2018-2019.	As above.
Firm sectoral uncertainty	Average uncertainty of the firm's NAICS-3 industry, computed as the average text-based uncertainty across public firms in that industry.	Authors' calculations using Hassan et al. (2019)
Firm in high-uncertainty sector	Dummy variable taking a value of one for the firms in NAICS-3 industries with uncertainty above the 75th percentile.	As above.
Firm bank debt	Total bank debt computed at the firm level as the sum of loans—term loans and credit lines—from Y-14 banks.	Authors' calculations using Y-14
Firm bank debt share	Share of bank loans (the sum of loans from Y-14 banks—term loans and credit lines) in the firm's total debt; average during 2016–2017.	Authors' calculations using Y-14
Investment rate	Yearly log change in the stock of fixed assets divided by lagged total assets.	Authors' calculations using Y-14
Firm total debt (asset) growth	Yearly log change in total debt (assets).	Authors' calculations using Y-14
Credit line utilization	Average credit line utilization rate, defined as the ratio of utilized loan amount to committed loan amount, aggregated from loan-level data at the firm level.	Authors' calculations using Y-14
Firm in oil sector	Firms in the NAICS-2 sector "Mining, quarrying, and oil and gas extraction."	Authors' calculations using Y-14
Exporter with retaliatory tariffs	Exporting firms with at least one product hit by retaliatory tariffs during 2018-2019.	Alfaro et al. (2025)
Firm is high-yield	Dummy variable taking a value of one for the firms with speculative grade rating, that is, with a maximum rating of BB on the S&P scale, across loans.	Authors' calculations using Y-14

Table OA.2. Descriptive statistics—Additional analyses

This table reports selected summary statistics at the bank level (panel A), loan level (panel B), and firm level (panel C), respectively, for additional analyses and robustness checks. Values for all growth rates are reported in decimals. See Section 3 for data descriptions, Section 3.2 for details on the construction of bank exposure to trade uncertainty and tariff measures, and Table OA.1 for variable definitions and sources.

	N	Mean	St. Dev.	P25	P50	P75
(A) Bank-level data						
Loan loss reserves (% gross loans, ppts)	457	1.216	0.797	0.964	1.129	1.349
Non-performing loans (% gross loans, ppts)	457	1.294	0.970	0.795	1.128	1.480
Net charge-offs (% gross loans, ppts)	457	0.747	1.183	0.268	0.452	0.618
Bank specialization measures for robustness checks:						
Bank specialization (Paravisini et al., 2023)	449	0.250	0.433	0.000	0.000	1.000
Bank specialization (Blickle et al., 2023)	449	1.413	1.071	0.777	1.158	1.617
Bank exposure to sanctioned countries	449	0.020	0.054	0.000	0.000	0.004
Bank exposure to non-trade uncertainty	449	-0.140	0.192	-0.252	-0.183	0.002
Bank loan portfolio cyclicality	449	1.186	1.127	0.661	1.075	1.431
Bank exposure to tradable-goods sectors	449	0.044	0.118	0.000	0.000	0.000
Bank exposure to trade uncertainty (leave-one-sector-out)	449	1.778	0.231	1.649	1.792	1.880
(B) Loan-level data						
Loan is credit line	620333	0.640	0.480	0.000	1.000	1.000
Loan is floating-rate	683999	0.965	0.185	1.000	1.000	1.000
Time to maturity (years)	683999	2.902	1.761	1.500	3.000	4.250
Loan is secured	682990	0.698	0.459	0.000	1.000	1.000
New loan origination	683999	0.069	0.254	0.000	0.000	0.000
New loan (originations and renewals)	683999	0.122	0.327	0.000	0.000	0.000
New loan (originations and modifications)	683999	0.367	0.482	0.000	0.000	1.000
Loan growth (utilization) - credit lines	185054	-0.329	1.446	-0.814	-0.038	0.373
Loan growth (utilization) - term loans	171989	-0.119	0.994	-0.502	-0.038	0.369
(C) Firm-level data						
Firm size (log-assets)	67664	17.861	2.202	16.293	17.346	18.959
Firm leverage (debt/assets)	67664	0.355	0.257	0.154	0.316	0.512
Firm cash holdings (cash/assets)	67664	0.104	0.131	0.015	0.056	0.145
Firm tangibility (tangible assets/assets)	67664	0.891	0.192	0.879	0.987	1.000
Firm return on assets	67664	15.107	19.752	5.816	11.275	18.703
Firm sales growth	67664	0.094	0.375	-0.027	0.037	0.122
Firm is high-yield	67664	0.621	0.485	0.000	1.000	1.000

Table OA.3. Changes in trade uncertainty by sector

This table reports the NAICS-3 sectors in the top and bottom quartiles of the distribution of changes in average trade uncertainty between 2016–2017 and 2018–2019. Trade uncertainty the frequency of mentions of synonyms for risk or uncertainty related bigrams, divided by transcript length and multiplied by 1,000. Tariff-hit is an indicator for the sectors that received tariffs during 2018–2019. The sector "Apparel manufacturing" (code 315) is omitted from the table due to extreme value for uncertainty driven by earnings transcript of a single firm. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources.

Sector code	**A. Largest increases in trade uncertainty**	**Δ Trade uncertainty**	**Sector is tariff-hit 0/1**
313	Textile Mills	5447.8	1
485	Transit and Ground Passenger Transportation	2420.6	0
482	Rail Transportation	1567.7	0
314	Textile Product Mills	1565.6	1
811	Repair and Maintenance	1503.8	0
532	Rental and Leasing Services	1268.3	0
483	Water Transportation	940.3	0
331	Primary Metal Mfg	925.5	1
333	Machinery Mfg	619.5	1
445	Food and Beverage Retailers	454.0	0
519	Web Search Portals, Libraries, Archives, Other Info Services	443.5	0
621	Ambulatory Health Care Services	427.2	0
112	Animal Production and Aquaculture	408.9	0
334	Computer and Electronic Product Mfg	401.3	1
	B. Largest decrease in trade uncertainty		
812	Personal and Laundry Services	-1113.7	0
488	Support Activities for Transportation	-792.4	0
493	Warehousing and Storage	-760.0	0
492	Couriers and Messengers	-685.4	0
335	Electrical Equipment, Appliance, and Component Mfg	-462.2	1
236	Construction of Buildings	-404.0	0
531	Real Estate	-180.4	0
623	Nursing and Residential Care Facilities	-126.4	0
423	Merchant Wholesalers, Durable Goods	-80.3	0
339	Miscellaneous Mfg	-72.4	1
322	Paper Mfg	-71.8	1
562	Waste Management and Remediation Services	-68.8	0
622	Hospitals	-64.0	0
332	Fabricated Metal Product Mfg	-51.8	1
312	Beverage and Tobacco Product Mfg	-41.4	1
722	Food Services and Drinking Places	-20.4	0

Table OA.4. Trade uncertainty and bank lending: Main specifications with all controls

This table shows OLS estimates for the main specifications (columns 3-4) in baseline Table 3 that include all estimated coefficients on control variables. Specification and controls are as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)
Dependent variable:	**Loan growth**	**Loan spread**
Bank exposure to trade uncertainty×Post	-0.278**	0.338***
	(0.121)	(0.118)
Bank exposure to tariff-hit sectors×Post	0.514*	0.264
	(0.284)	(0.237)
Size (log-assets)	0.084	-0.098
	(0.057)	(0.151)
Capital ratio (common equity/assets)	-1.608	0.051
	(1.779)	(1.753)
Core deposits/assets	0.207	-0.300
	(0.245)	(0.371)
Bank specialization	0.009	-0.007
	(0.011)	(0.011)
Size (log-assets)×Post	-0.002	-0.036*
	(0.015)	(0.020)
Capital ratio (common equity)×Post	0.969	0.314
	(0.913)	(1.473)
Core deposits/assets×Post	-0.043	-0.047
	(0.110)	(0.122)
Bank specialization×Post	0.009	-0.007
	(0.011)	(0.011)
Observations	683,999	357,187
R-squared	0.342	0.850
Bank controls×Post	Y	Y
Firm×Bank FE	Y	Y
Firm×Quarter FE	Y	Y

Table OA.5. Placebo test and anticipation effects

This table reports additional robustness checks for the main specifications (columns 3-4) in baseline Table 3. In panel A we modify the sample period for a placebo test that compares lending outcomes (loan growth and spreads) during 2013–2014 versus 2015–2016. In panel B, we drop all loan commitments in 2017 and compare lending outcomes during 2015 versus 2018–2019. Specification and controls as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**
	(A) Placebo test 2013–2014 vs 2015–2016	
Bank exposure to trade uncertainty×Post	0.057	-0.404**
	(0.041)	(0.185)
Bank exposure to tariff-hit sectors×Post	-0.201*	-1.379***
	(0.098)	(0.390)
Observations	628,290	329,194
R-squared	0.675	0.836
	(B) Anticipation effects (drop 2017)	
Bank exposure to trade uncertainty×Post	-0.280**	0.414***
	(0.129)	(0.145)
Bank exposure to tariff-hit sectors×Post	0.573*	0.310
	(0.317)	(0.303)
Observations	509,239	264,331
R-squared	0.352	0.846
Bank controls×Post	Y	Y
Firm×Quarter FE	Y	Y
Firm×Bank FE	Y	Y

Table OA.6. Trade uncertainty and additional lending outcomes: Loan maturity, collateral requirements, and new loans

This table shows OLS estimates for the main specifications (columns 3-4) of baseline Table 3 where the dependent variables are loan remaining maturity (time to maturity, log), collateral requirements (a dummy variable for secured loans), and a dummy variable for new loan originations. Panel A uses bank or firm×bank fixed effects and Khwaja-Mian (firm×quarter) fixed effects, while panel B only includes bank, firm, and quarter fixed effects. Specification and controls otherwise as in Table 3. Specification in column 1 controls for additional loan characteristics, including loan size (log-committed amount), dummy variable for secured loans, and dummy variable for floating-rate loans. Specification in column 2 also controls for additional loan characteristics, including loan size (log-committed amount), loan maturity, and dummy variable for floating-rate loans. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Time to maturity (log)**	(2) **Loan is Secured (0/1)**	(3) **New Loan Origination (0/1)**
	(A) With Khwaja-Mian FE		
Bank exposure to trade uncertainty×Post	-0.034**	0.066**	-0.016*
	(0.015)	(0.032)	(0.008)
Bank exposure to tariff-hit sectors×Post	0.031	0.062	0.013
	(0.045)	(0.056)	(0.022)
Observations	682,922	627,206	683,999
R-squared	0.720	0.901	0.507
Firm×Bank FE	Y	Y	-
Firm×Quarter FE	Y	Y	Y
Bank FE	-	-	Y
	(B) Without Khwaja-Mian FE		
Bank exposure to trade uncertainty×Post	-0.033*	0.064*	-0.007
	(0.016)	(0.036)	(0.012)
Bank exposure to tariff-hit sectors×Post	0.073	0.060	0.016
	(0.047)	(0.078)	(0.032)
Observations	682,989	635,932	683,999
R-squared	0.486	0.760	0.083
Bank controls×Post	Y	Y	Y
Bank FE	Y	Y	Y
Firm FE	Y	Y	Y
Quarter FE	Y	Y	Y

Table OA.7. Trade uncertainty and bank lending: Control for probability of default

This table shows OLS estimates for the main specifications (columns 3-4) of baseline Table 3 where we additionally control for the probability of default as assessed by the bank. Specification and controls as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)
Dependent variable:	**Loan growth**	**Loan spread**
Bank exposure to trade uncertainty×Post	-0.270**	0.274***
	(0.125)	(0.091)
Bank exposure to tariff-hit sectors×Post	0.517	0.360*
	(0.306)	(0.186)
Probability of default	-0.159**	-0.032
	(0.064)	(0.043)
Observations	641,698	332,315
R-squared	0.342	0.849
Bank controls×Post	Y	Y
Firm×Bank FE	Y	Y
Firm×Quarter FE	Y	Y

Table OA.8. New loans, single-lender firms, and syndicated loans

This table reports several variants for the baseline regressions in Table 3. In panels A and B we limit the sample to new loans (new originations and renewed loans) (panel A) or new loans and modified loans (panel B). New Modified loans are identified following Bidder et al. (2025) as those loans experiencing, in any given quarter, a change of at least 20 bps in the loan spread or at least one-quarter in the loan maturity. In panels C-D we explore additional sample splits. In panel C we repeat the estimation in the sample of loans corresponding to single-lender firms (those firms with a single bank relationship during 2016–2019). In panel D we drop, for the multi-lender firms sample, the firm-quarter observations with a single syndicated loan, given that these loans do not have any variation in the loan spread across lenders. Specification and controls as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Loan amount (log)**	**Loan spread**	**Loan growth**	**Loan spread**
I. Sample of New Loans	**(A) New loan originations**		**(B) New loan (originations and modifications)**	
Bank exposure to trade uncertainty×Post	-0.485***	0.343*	-0.223**	0.301**
	(0.120)	(0.185)	(0.099)	(0.131)
Bank exposure to tariff-hit sectors×Post	0.479	0.347	0.589**	0.449*
	(0.286)	(0.285)	(0.249)	(0.226)
Observations	66,447	30,486	219,618	167,695
R-squared	0.681	0.820	0.502	0.886
Bank controls×Post	Y	Y	Y	Y
Bank FE	Y	Y	-	-
Firm×Bank FE	-	-	Y	Y
Firm×Quarter FE	Y	Y	Y	Y

Dependent variable:	**Loan growth**	**Loan spread**	**Loan spread**
II. Additional Sample Splits	**(C) Single-lender firms**		**(D) Drop firm-quarter obs. with a single syndicated loan**
Bank exposure to trade uncertainty×Post	-0.052*	0.307*	0.340***
	(0.029)	(0.163)	(0.118)
Bank exposure to tariff-hit sectors×Post	0.189*	0.184	0.268
	(0.108)	(0.662)	(0.238)
Observations	1,023,606	611,028	351,905
R-squared	0.011	0.167	0.848
Bank controls×Post	Y	Y	Y
Bank FE	Y	Y	-
Sector×Quarter FE	Y	Y	-
State×Quarter FE	Y	Y	-
Firm×Bank FE	-	-	Y
Firm×Quarter FE	-	-	Y

Table OA.9. Robustness to alternative clustering of the standard errors

This table shows OLS estimates for the main specifications in Table 3 (columns 3-4) and Table OA.6 (columns 1-3, panel A) where the standard errors are estimated using alternative clustering approaches. The standard errors are single-clustered at the bank level in panel A and triple clustered at the bank, firm, and quarter level in panel B. Specification and controls are otherwise as in the main tables. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**	(3) **Time to maturity**	(4) **Loan is secured (0/1)**	(5) **New loan (0/1)**
	(A) Cluster on bank				
Bank exposure to trade uncertainty×Post	-0.2782**	0.3384**	-0.0344**	0.0662*	-0.0156*
	(0.1325)	(0.1316)	(0.0155)	(0.0348)	(0.0080)
Bank exposure to tariff-hit sectors×Post	0.5138	0.2641	0.0311	0.0617	0.0132
	(0.3114)	(0.2633)	(0.0465)	(0.0591)	(0.0231)
Observations	683,999	357,187	682,922	627,206	683,999
R-squared	0.3424	0.8495	0.7201	0.9006	0.5066
	(B) Cluster on bank, firm, and quarter				
Bank exposure to trade uncertainty×Post	-0.2782**	0.3384**	-0.0344*	0.0662*	-0.0156*
	(0.1233)	(0.1430)	(0.0168)	(0.0334)	(0.0077)
Bank exposure to tariff-hit sectors×Post	0.5138*	0.2641	0.0311	0.0617	0.0132
	(0.2773)	(0.2427)	(0.0495)	(0.0575)	(0.0225)
Observations	683,999	357,187	682,922	627,206	683,999
R-squared	0.3424	0.8495	0.7201	0.9006	0.5066
Bank controls×Post	Y	Y	Y	Y	Y
Firm×Bank FE	Y	Y	Y	Y	-
Firm×Quarter FE	Y	Y	Y	Y	Y
Bank FE	-	-	-	-	Y

Table OA.10. Additional results: Bank reallocation to other assets

This table shows OLS estimates for a regression of additional bank-level outcomes—share of residential real estate (RRE) loans, consumer loans, and cash in total assets—on bank exposure to uncertainty. The data are at the bank-quarter level during the period 2016–2019. Specification and controls otherwise as in Table 6. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the bank level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)	(3)
Dependent variable:	**RRE loans (% assets)**	**Consumer loans (% assets)**	**Cash (% assets)**
Bank exposure to trade uncertainty×Post	-0.016	-0.005	0.003
	(0.022)	(0.009)	(0.010)
Bank exposure to tariff-hit sectors×Post	0.004	-0.006	-0.027
	(0.056)	(0.022)	(0.025)
Observations	457	457	457
R-squared	0.985	0.997	0.971
Bank controls×Post	Y	Y	Y
Bank FE	Y	Y	Y
Quarter FE	Y	Y	Y

Table OA.11. Covariate balance for firms in high versus low-uncertainty sectors

This table presents a covariate balance test for firms with high versus low exposure to trade uncertainty (through their lenders) over the 2016–2017 period. Panels A and B report mean characteristics for firms split around the median and the 75th percentile. In column 3 we report standardized differences between each pair of averages, normalized by the square root of the sum of the corresponding variances. Imbens and Rubin (2015) propose that two variables have "similar" means when the absolute normalized difference is less than 0.25. Significance: * indicates that the absolute normalized difference is greater than 0.25 and hence the two means are "different."

	(1) **High uncertainty firm**	(2) **Low uncertainty firm**	(3) **Standardized difference (2)-(1)**
(A) Around the median of uncertainty	**N=8,652**	**N=11,122**	
Firm in tariff-hit sector	0.346	0.224	-1.609*
Total debt growth	0.040	0.056	0.035
Investment rate	0.063	0.084	0.049
Total asset growth	0.057	0.073	0.062
Total assets (bn)	0.976	2.192	0.083
Cash holdings (cash/assets)	0.348	0.367	0.075
Leverage (debt/assets)	0.112	0.095	-0.129
Tangibility (tangible assets/assets)	0.917	0.871	-0.243
Return on assets	15.120	14.727	-0.020
Real sales growth	0.126	0.070	-0.129
Firm is high yield	0.666	0.574	-0.191
(B) Around the 75th percentile of uncertainty	**N=3,702**	**N=16,072**	
Firm in tariff-hit sector	0.284	0.272	-0.686*
Total debt growth	0.049	0.053	0.067
Investment rate	0.086	0.074	0.022
Total asset growth	0.067	0.065	0.031
Total assets (bn)	1.477	1.723	0.061
Cash holdings (cash/assets)	0.357	0.362	0.103
Leverage (debt/assets)	0.104	0.101	-0.071
Tangibility (tangible assets/assets)	0.896	0.889	-0.175
Return on assets	14.768	14.990	0.059
Real sales growth	0.090	0.098	0.098
Firm is high yield	0.600	0.621	0.168

Table OA.12. Real effects: Robustness to aggregated data

This table shows OLS estimates an aggregated version of the main real effects specifications in Table 7. The data are aggregated from the firm-year level to the NAICS3 sector-county-year level in all specifications, except column 2 where the data are on quarterly frequency. Specification and controls otherwise as in Table 7. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the county level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Total debt growth**	(2) **Bank debt growth**	(3) **Investment rate**	(4) **Asset growth**
	(A) Level effect			
Sector-county exposure to trade uncertainty×Post	-0.125***	-0.067	-0.165***	-0.118***
	(0.032)	(0.049)	(0.034)	(0.022)
Sector-county exposure to tariff-hit sectors×Post	0.738***	0.035	0.838***	0.586***
	(0.160)	(0.242)	(0.187)	(0.116)
Observations	14,721	147,607	14,715	14,719
R-squared	0.113	0.043	0.114	0.134
	(B) By sector-county with higher or lower bank debt share			
Sector-county exp. to trade unc.×Post×Higher bank debt share [1]	-0.163***	-0.093*	-0.185***	-0.132***
	(0.032)	(0.050)	(0.035)	(0.022)
Sector-county exp. to trade unc.×Post×Lower bank debt share [2]	-0.109***	-0.053	-0.156***	-0.113***
	(0.032)	(0.050)	(0.034)	(0.023)
Sector-county exposure to tariff-hit sectors×Post	0.709***	0.010	0.823***	0.576***
	(0.161)	(0.246)	(0.188)	(0.116)
p-value t-test: $H_a : \|1\| > \|2\|$	0.000	-	0.000	0.000
Observations	14,721	144,578	14,715	14,719
R-squared	0.118	0.041	0.116	0.135
County controls×Post	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

Table OA.13. Real effects: Robustness to more granular sector cells

This table shows OLS estimates for the main real effects specifications in Table 7 with finer sector cells. Whereas in Table 7 we use 3-digit NAICS industry classification, here we use 4-digit (panel A) and 6-digit (panel B) industry classification, respectively. Specification and controls are otherwise as in Table 7. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) Total debt growth	(2) Bank debt growth	(3) Investment rate	(4) Asset growth	(5) Total debt growth	(6) Bank debt growth	(7) Investment rate	(8)) Asset growth
I. Level effect	**(A) Robustness to 4-digit NAICS**				**(B) Robustness to 6-digit NAICS**			
Firm exposure to trade uncertainty×Post	-0.063**	-0.208***	-0.081***	-0.058***	-0.050*	-0.191**	-0.106***	-0.062***
	(0.025)	(0.078)	(0.029)	(0.015)	(0.029)	(0.093)	(0.035)	(0.018)
Firm exposure to tariff-hit sectors×Post	0.113	0.441	0.377**	0.185**	0.088	0.164	0.454**	0.159*
	(0.127)	(0.375)	(0.151)	(0.073)	(0.149)	(0.436)	(0.183)	(0.092)
Observations	51,229	173,055	50,192	51,139	39,095	133,133	38,206	39,039
R-squared	0.638	0.489	0.603	0.677	0.659	0.509	0.621	0.689
II. By bank debt share								
Firm exp. to trade unc.×Post×Higher bank debt share [1]	-0.076***	-0.313***	-0.084***	-0.062***	-0.065**	-0.304***	-0.104***	-0.066***
	(0.025)	(0.080)	(0.029)	(0.015)	(0.030)	(0.095)	(0.036)	(0.019)
Firm exp. to trade unc.×Post×Lower bank debt share [2]	-0.054**	-0.228***	-0.080***	-0.056***	-0.043	-0.217**	-0.105***	-0.060***
	(0.025)	(0.078)	(0.029)	(0.015)	(0.029)	(0.093)	(0.035)	(0.018)
Firm exp. to tariff-hit sectors×Post	0.085	0.323	0.374**	0.175**	0.074	0.158	0.452**	0.149
	(0.128)	(0.371)	(0.152)	(0.074)	(0.150)	(0.434)	(0.184)	(0.093)
p-value t-test: $H_a : \|1\| > \|2\|$	0.000	0.000	0.245	0.055	0.002	0.000	0.466	0.091
Observations	50,690	172,014	49,667	50,600	38,661	132,321	37,793	38,605
R-squared	0.637	0.491	0.602	0.676	0.658	0.511	0.619	0.688
p-value t-test: $H_a : \|1\| > \|2\|$	0.000	0.000	0.245	0.055	0.002	0.000	0.466	0.091
Firm controls×Post	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Sector×County×Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Table OA.14. Evidence on credit demand shifts based on firm exposure to uncertainty

This table shows OLS estimates for the main specifications (columns 3-4) in baseline Table 3 where the difference-in-differences coefficient is broken down by firm exposure to uncertainty. The variable "Firm in high-uncertainty sector" is a dummy variable taking a value of one for the firms in NAICS-3 industries with above-median change in average uncertainty between 2016–2017 and 2018–2019. Specification and controls are as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**
Bank exp. to trade unc.×Post×Firm in low-unc. sector [1]	-0.270**	0.326***
	(0.128)	(0.118)
Bank exp. to tariff-hit sectors×Post×Firm in high-unc. sector [2]	-0.280**	0.345***
	(0.122)	(0.123)
Bank exposure to tariff-hit sectors×Post	0.504*	0.290
	(0.287)	(0.245)
p-value t-test: $H_o : \|1\| = \|2\|$	0.826	0.652
Observations	654,863	345,972
R-squared	0.339	0.848
Bank controls×Post	Y	Y
Firm×Bank FE	Y	Y
Firm×Quarter FE	Y	Y

Table OA.15. Evidence on credit demand shifts from loan utilizations

This table shows OLS estimates for regressions of utilized loan growth and credit line utilization rate on bank and firm exposure to trade uncertainty, respectively. In columns 1-2, the dependent variable is utilized loan growth, defined the same as committed loan growth in baseline Table 3 as the log-difference between the utilized amount at time t and that at the start of the sample (2016:Q1) for a given bank-firm pair. In columns 3–4, the dependent variable is the credit line utilization rate, computed as the ratio of utilized credit to total committed credit. The data are at the loan level (columns 1–2) or firm-level (columns 3–4) during the period of 2016–2019. Loan samples refer to credit lines (columns 1, 3), term loans (column 2), and drawn credit lines with positive utilization rate (column 4). The variable "Firm in high-uncertainty sector" is a dummy variable taking a value of one for the firms in NAICS-3 industries with above-median change in average uncertainty between 2016–2017 and 2018–2019. In columns 1-2, specification and other controls as in Table 3. In columns 3-4, specification and other controls as in Table 7. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double-clustered at the bank and firm level in panel A and clustered at the firm level in panel B. Significance: *** 1%, **5%, and *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Utilized loan growth**		**Credit line utilization rate**	
	(A) Loan-level		**(B) Firm-level**	
	Credit lines	**Term loans**	**Credit lines**	**Drawn credit lines**
Bank exposure to trade uncertainty×Post	-0.167	0.013		
	(0.136)	(0.066)		
Bank exposure to tariff-hit sectors×Post	0.507	0.301		
	(0.337)	(0.217)		
Firm in high-uncertainty sector×Post			0.0015	0.0006
			(0.0019)	(0.0023)
Firm in tariff-hit sector× Post			0.0149***	0.0146***
			(0.0024)	(0.0028)
Observations	185,054	171,989	569,628	388,432
R-squared	0.682	0.637	0.8192	0.7672
Bank controls×Post	Y	Y	-	-
Firm×Bank FE	Y	Y	-	-
Firm×Quarter FE	Y	Y	-	-
Firm controls×Post	-	-	Y	Y
Firm FE	-	-	Y	Y
County×Quarter FE	-	-	Y	Y

Table OA.16. Trade uncertainty and banks' loan losses

This table shows OLS estimates for a regression of bank asset quality on bank exposure to trade uncertainty. The dependent variables are the loan loss reserve ratio, nonperforming loan ratio, and net charge-off ratio (all computed relative to total gross loans). The data are at the bank-quarter level for the period 2016–2019. Specification and controls are as in baseline Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are clustered at the bank level. Significance: *** 1%, **5%, and *10%.

	(1)	(2)	(3)
Dependent variables:	**Loan loss reserves**	**Non-performing loans**	**Net charge-offs**
Bank exposure to trade uncertainty×Post	-0.028	0.355	-0.047
	(0.107)	(0.226)	(0.128)
Bank exposure to tariff-hit sectors×Post	-0.464	0.272	-0.626*
	(0.288)	(0.567)	(0.343)
Observations	457	457	457
R-squared	0.988	0.944	0.969
Bank controls×Post	Y	Y	Y
Bank FE	Y	Y	Y
Quarter FE	Y	Y	Y

Table OA.17. Robustness to alternative measures of bank specialization

This table reports additional robustness checks for the main specifications (columns 3-4) in baseline Table 3. In panels A and B we modify the measure of bank specialization as a control variable using alternative definitions of bank specialization from Paravisini et al. (2023) and Blickle et al. (2023), respectively. In panel C we include firm×loan purpose×year fixed effects to allow for the possibility that some banks may specialize in certain types of lending. Following Greenwald et al. (2024), we consider the categories "acquisitions and merger financing", "working capital (short-term and permanent)", "real estate investments or acquisitions," and all other loan purposes. In panel D, we include additional firm×trade finance×year fixed effects to allow for the possibility that some banks may specialize in trade financing (letters of credit and loan performance guarantees). "Trade finance" takes a value of one for loans with "trade financing" purpose and zero otherwise. Specification and other controls as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**	(3) **Loan growth**	(4) **Loan spread**
	(A) Paravisini et al. (2023) specialization		**(B) Blickle et al. (2023) specialization**	
Bank expsure to trade uncertainty×Post	-0.281**	0.344***	-0.271**	0.342***
	(0.123)	(0.122)	(0.118)	(0.120)
Bank exposure to tariff-hit sectors×Post	0.507*	0.281	0.518*	0.276
	(0.283)	(0.244)	(0.280)	(0.242)
Bank specialization×Post	-0.011	0.029	-0.013	-0.011
	(0.022)	(0.036)	(0.008)	(0.014)
Observations	683,999	357,187	683,999	357,187
R-squared	0.342	0.850	0.342	0.850
Bank controls×Post	Y	Y	Y	Y
Firm×Quarter FE	Y	Y	Y	Y
Firm×Bank FE	Y	Y	Y	Y
	(C) Firm×Loan purpose×Year fixed effects		**(D) Firm×Trade finance purpose ×Year fixed effects**	
Bank exposure to trade uncertainty×Post	-0.167*	0.292***	-0.249**	0.328***
	(0.094)	(0.105)	(0.107)	(0.116)
Bank exposure to tariff-hit sectors×Post	0.614***	0.315	0.405	0.256
	(0.209)	(0.200)	(0.252)	(0.243)
Observations	671,696	346,896	683,120	356,663
R-squared	0.471	0.888	0.371	0.851
Bank controls×Post	Y	Y	Y	Y
Firm×Quarter FE	Y	Y	Y	Y
Firm×Bank FE	Y	Y	Y	Y
Firm×Loan purpose×Year FE	Y	Y	Y	Y

Table OA.18. Control for sanctions, retaliatory tariffs, commodity price fluctuations, and exchange rates

This table reports additional tests to gauge the robustness of our main specifications in columns 3-4 of baseline Table 3. In panels A and B we control for bank exposure to foreign borrowers in countries on which the United States imposed sanctions during the sample period (panel A) and dropping exporting firms who face retaliatory tariffs (on at least one export product) during 2018–2019 (panel B). In panels C and D we control for bank exposure to concurrent macroeconomic developments such as commodity price fluctuations (by dropping firms in the NAICS-2 "Mining, Quarrying, and Oil and Gas Extraction" industry) (panel C) or exchange rate movements by interacting bank exposure to tradable-goods sectors with the U.S. Dollar broad index (panel D). specification and controls are otherwise as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**	(3) **Loan growth**	(4) **Loan spread**
	(A) Control for bank exposure to sanctioned countries		**(B) Drop exporters that face retaliatory tariffs**	
Bank exposure to trade uncertainty×Post	-0.204**	0.300**	-0.281**	0.337***
	(0.099)	(0.114)	(0.119)	(0.117)
Bank exposure to trade uncertainty×Post	0.423*	0.264	0.519*	0.268
	(0.231)	(0.242)	(0.281)	(0.235)
Observations	683,999	357,187	677,437	353,434
R-squared	0.342	0.850	0.343	0.850
	(C) Drop oil firms		**(D) Exchange rates**	
Bank exposure to trade uncertainty×Post	-0.286**	0.313**	-0.279**	0.343***
	(0.120)	(0.114)	(0.121)	(0.118)
Bank exposure to trade uncertainty×Post	0.460	0.243	0.514*	0.267
	(0.272)	(0.227)	(0.284)	(0.238)
Bank exp. to tradable-goods sectors×USD broad index			0.011	-0.032***
			(0.007)	(0.009)
Observations	639,939	329,591	683,999	357,187
R-squared	0.337	0.849	0.342	0.850
Bank controls×Post	Y	Y	Y	Y
Firm×Quarter FE	Y	Y	Y	Y
Firm×Bank FE	Y	Y	Y	Y

Table OA.19. Additional robustness checks: Controlling for non-trade exposure, loan portfolio cyclicality, loan collateral type, and results by loan type

This table reports additional robustness checks for the main specifications (columns 3-4) of baseline Table 3. In panel A we replace our baseline measure of bank exposure to trade uncertainty with a measure of bank exposure to non-trade uncertainty, where non-trade uncertainty index is obtained as the first principal component of all uncertainty indices for sectors other than trade. In panel B we control for the cyclicality of banks' lending portfolios measured as the degree of co-movement between a bank's C&I loan portfolio and aggregate banking sector assets. In panel C we re-estimate the main specifications with loan collateral type fixed effects, where collateral types are (a) unsecured loans, (b) asset-based loans, and (c) earnings-based loans, and classified following Caglio et al. (2024). In panel D we break down the main difference-in-differences term by loan type: credit lines versus term loans. Specification and controls are otherwise as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**	(3) **Loan growth**	(4) **Loan spread**
	(A) Control for bank exposure to non-trade uncertainty		**(B) Control for cyclicality of bank's loan portfolio**	
Bank exposure to trade uncertainty×Post	-0.298**	0.288**	-0.230**	0.330**
	(0.113)	(0.112)	(0.107)	(0.134)
Bank exposure to non-trade uncertainty×Post	0.188	0.400**		
	(0.120)	(0.173)		
Bank cylicality×Post			0.028***	-0.009
			(0.009)	(0.043)
Bank exposure to tariff-hit sectors×Post	0.841**	1.150**	0.550*	0.256
	(0.367)	(0.537)	(0.275)	(0.239)
Observations	683,999	357,187	683,999	357,187
R-squared	0.342	0.850	0.342	0.850
	(C) Collateral type×year FE		**(D) Credit lines vs. Term loans**	
Bank exposure to trade uncertainty×Post	-0.197*	0.314**		
	(0.100)	(0.118)		
Bank exposure to trade uncertainty×Post×Credit line			-0.202	0.306**
			(0.133)	(0.123)
Bank exposure to trade uncertainty×Post×Term loan			-0.336**	0.419***
			(0.142)	(0.121)
Bank exposure to tariff-hit sectors×Post	0.489*	0.233	0.593*	0.355
	(0.258)	(0.253)	(0.337)	(0.232)
Observations	683,999	357,187	612,015	338,886
R-squared	0.362	0.850	0.372	0.873
Bank controls×Post	Y	Y	Y	Y
Firm×Quarter FE	Y	Y	Y	Y
Firm×Bank FE	Y	Y	Y	Y

Table OA.20. Additional robustness checks: Alternative estimator and bank exposure to uncertainty measure

This table reports additional robustness checks for the main specifications (columns 3-4) of baseline Table 3. In panel A, we report results from a Weighted Least Squares (WLS) estimation with analytical weights given by the bank-specific average firm count on the basis of which we compute sectoral uncertainty and in turn bank exposure to uncertainty. The WLS estimator thus gives a greater weight to banks for which exposures to uncertainty are computed from sectors with more listed firms (for which trade uncertainty reports are available) and it gives a lower weight to banks whose exposure measure draws on less uncertainty information. In panel B we replace our baseline measure of bank exposure to trade uncertainty with an alternative measure constructed at the bank-sector level by leaving one-sector-out at a time, suggested by Borusyak et al. (2022). Specification and controls are otherwise as in Table 3. See Section 3 for data descriptions and Table OA.1 for variable definitions and sources. Standard errors are double clustered at the bank and firm level. Significance: *** 1%, **5%, and *10%.

Dependent variable:	(1) **Loan growth**	(2) **Loan spread**	(3) **Loan growth**	(4) **Loan spread**
	(A) Weighted least squares		**(B) "Leave-one-sector-out" baseline exposure**	
Bank exposure to trade uncertainty×Post	-0.350**	0.396***	-0.207**	0.277***
	(0.140)	(0.114)	(0.087)	(0.095)
Bank exposure to tariff-hit sectors×Post	0.650**	0.218	0.436*	0.315
	(0.312)	(0.219)	(0.248)	(0.229)
Observations	683,999	357,187	683,999	357,187
R-squared	0.350	0.855	0.342	0.849
Bank controls×Post	Y	Y	Y	Y
Firm×Quarter FE	Y	Y	Y	Y
Firm×Bank FE	Y	Y	Y	Y