

## Trade Uncertainty and U.S. Bank Lending

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**Abstract:** This paper uses U.S. credit register data and the 2018–19 Trade War to study the effects of uncertainty on domestic credit supply. Exploiting differences in banks’ ex-ante exposure to trade uncertainty, we find that increased uncertainty is associated with a broad lending contraction across their customer firms. This result is consistent with banks responding to uncertainty with wait-and-see behaviors, where more exposed banks curtail risky exposures, reduce loan maturities, and adjust loan supply along both intensive and extensive margins. The lending contraction is larger for more capital-constrained banks and has significant real effects, especially for bank-dependent firms.

JEL classification: G21, F34, F42

Key words: uncertainty, bank loans, trade finance, credit supply, trade war

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# 1 Introduction

Concerns about trade uncertainty have been on the rise given events such as Brexit, the Covid-19 pandemic, and recent trade tensions. Whereas it is well understood that a rise in uncertainty increases the spread of project returns faced by firms, which in turn affects their investment behavior,<sup>1</sup> the effects of uncertainty, and trade uncertainty specifically, on financial intermediaries is less clear. In particular, the channels through which uncertainty shocks affect bank lending may differ from how first-moment shocks to borrowers or bank balance sheets operate, on which the literature traditionally focuses.<sup>2</sup> Against this backdrop, we ask if and how international trade uncertainty is propagated by banks to the domestic economy. Additionally, we seek to understand the mechanisms through which uncertainty more broadly affects credit supply.

We assess the effects of uncertainty on U.S. banks' credit supply by exploiting the sharp rise in trade uncertainty that occurred during the 2018–2019 escalation of trade tensions between the U.S. and some of its trading partners, which has been referred to as a “Trade War.” Unlike a negative sectoral shock that could lead banks to shift credit away from that sector,<sup>3</sup> an uncertainty shock widens the distribution of loan returns within and across sectors and may lead banks to curtail lending more broadly. We investigate this possibility utilizing a measure of bank-specific exposure to uncertainty that combines firm-level information on trade uncertainty with detailed data on U.S. banks' loan exposures to domestic borrowers. We exploit the cross-sectional bank heterogeneity in this exposure to test for the credit *supply* effect of an increase in uncertainty and hypothesize that banks' lending decisions might be driven by a “wait-and-see” strategy, whereby the exposed banks are more prone to pull back from risk-taking. The size of this response might also be driven by a financial frictions channel by which banks' credit supply depends on their capital levels. Finally, we ask whether the estimated changes in credit supply have real effects on firms.

Our first novel finding is that an increase in uncertainty is associated with a larger credit contraction at the bank-firm level for more exposed banks, that is, those banks with a larger ex-

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<sup>1</sup>For example, see a textbook treatment by [Dixit and Pindyck \(1994\)](#).

<sup>2</sup>See, for example, [Peek and Rosengren \(2000\)](#); [Khwaja and Mian \(2008\)](#); [Ivashina and Scharfstein \(2010\)](#); [Cornett et al. \(2011\)](#); [Puri et al. \(2011\)](#); [Giannetti and Laeven \(2012\)](#); [De Haas and Van Horen \(2013\)](#); [Chodorow-Reich \(2014\)](#); [Iyer et al. \(2014\)](#); [Popov and Van Horen \(2015\)](#); [Gilje et al. \(2016\)](#); [Amiti and Weinstein \(2018a\)](#); [Ongena et al. \(2018\)](#); [Galaasen et al. \(2021\)](#); [Bidder et al. \(2021\)](#); [Mayordomo and Rachedi \(2022\)](#); [Federico et al. \(2023a,b\)](#).

<sup>3</sup>This reallocation would depend, among others, on bank capital constraints and cross-correlations of sectoral returns ([Holmstrom and Tirole, 1997](#); [Froot and Stein, 1998](#); [DeYoung et al., 2015](#)).

ante share of loans to firms in sectors facing a greater increase in trade uncertainty. This result holds even when we restrict the sample to borrowers that are relatively less exposed to an increase in trade uncertainty. Second, the contraction in credit supply is not driven by realized losses in banks’ portfolios, but rather by difficulties predicting future loan returns due to the rise in uncertainty, and is stronger for banks with lower capital buffers. The findings are consistent with banks responding to uncertainty with wait-and-see behaviors, where more exposed banks curtail risky exposures, charge higher spreads, and reduce loan maturities. Third, the real outcomes for firms are worse when they borrow from the more exposed banks and when they are more reliant on bank credit.

Our analysis uses a comprehensive loan-level data set collected through the Federal Reserve (FR) Y-14Q form (known as the “U.S. credit register”). The data comprise of quarterly bank-firm loan commitments to domestic (public and private) firms by large U.S. banks. We use this data set to examine a wide range of lending outcomes and to construct our key measure of bank exposure to trade uncertainty, which combines loan exposures with firm-level measures of trade uncertainty. Firm-level trade uncertainty measures are sourced from [Hassan et al. \(2019, 2020a,b\)](#) and are based on textual analysis of the transcripts of listed firms’ quarterly earnings calls. Given that the firms in the credit register and those spanned by the transcript data do not overlap perfectly, we take a three-step approach in constructing our measure of bank exposure to trade uncertainty. First, we aggregate the firm-level uncertainty measures to the 3-digit NAICS sector-level.<sup>4</sup> Second, we assign these sector-level uncertainty measures to borrowers in the credit register based on their sectoral classification. Finally, we aggregate this information at the bank level by taking the average change in uncertainty between 2016–2017 and 2018–2019 across sectors, weighted by initial loan shares in a given sector. The loan shares are taken to be averages over 2014–2015 so they are lagged relative to the start of the sample and hence unlikely affected by the 2018–2019 Trade War. This approach makes the bank exposure measure more likely predetermined with respect to economic conditions during the sample period.

We use a difference-in-differences estimation framework. Our baseline specification regresses the growth rate in outstanding loans at the bank-firm loan level on the measure of bank exposure to

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<sup>4</sup>We do this to maximize coverage of firms within the Y-14Q data as the firm-level uncertainty measures are constructed from a more limited set of publicly listed firms. We check whether our baseline results are robust in a weighted-least square regression that controls for the underlying size of the firm sample used in constructing the sector-level measure.

trade uncertainty interacted with a *Post* dummy taking the value of one for the years of heightened trade uncertainty in 2018 and 2019, and zero for the years 2016 and 2017. To corroborate that the shifts in loan quantities are consistent with a shift in the supply of credit, we estimate complementary specifications using loan spreads as the dependent variable. We make sure that our results are not confounded by standard determinants of banks' lending decisions by controlling for bank size, capital, core deposits, and sectoral specialization (defined as in [Paravisini et al., 2023](#)) in levels and interacted with the *Post* dummy. We further show that the bank exposure measure is unrelated to these control variables in each yearly cross-section of banks over the sample period, which provides additional support to the validity of the assumption that the bank exposure measure is unrelated to other bank attributes that might also affect lending.

We have three sets of main results. Our first result, that an increase in uncertainty is associated with a larger credit contraction for more exposed banks, is consistent with real-options theory whereby non-financial firms respond to increased uncertainty by adopting a wait-and-see attitude ([Dixit and Pindyck, 1994](#)). More exposed banks are less likely to grant new loans than other banks, reduce loan growth, and charge higher spreads. This credit contraction manifests vis-à-vis *all* borrowers, including those that are less directly exposed to an increase in trade uncertainty. In addition, more exposed banks reduce the maturity of loans and are more likely to grant loans that can be called in early (so-called demandable loans).

The second set of results explores the effect of bank capital buffers on their credit supply when uncertainty increases. A financial constraints channel is supported as well, as exposed banks with lower levels of current and stressed capital levels contract their lending by more than other banks. Consistent with exposed banks reducing their risky portfolio share as uncertainty increases, we find that exposed banks rebalance their balance sheets away from commercial loans and also into safer assets, notably securities. In addition, we show that exposed banks are more likely to downgrade the perceived creditworthiness of their borrowers, as reflected in higher assessed probabilities of default, but do not experience higher loan delinquencies and do not increase loan loss reserves. These results are consistent with the notion that uncertainty, by generating a wider dispersion in loan returns, creates difficulties in banks' assessment of potential gains or losses, with material effects on their lending decisions, even in the absence of a realized balance sheet shock.

The third set of results focuses on the consequences of exposed banks' credit contraction for the

real sector. We test whether firms that are more exposed to trade uncertainty through their banks are also affected. We find that the more exposed firms are unable to substitute for reduced bank lending through alternative sources of finance, and these firms exhibit lower total debt growth and investment rates. Furthermore, firms with a higher share of bank debt and private firms—more likely to depend on bank financing—experience relatively worse real outcomes, which confirms that banks serve as a conduit for amplifying the effects of uncertainty on the domestic economy.

The credit supply contraction is economically meaningful. Our point estimates in the full sample of firms imply that a one standard deviation increase in bank exposure to trade uncertainty is associated with a 2.6 percentage point (ppt) decline in loan growth (compared to 0% median loan growth for the sample), a 6.5 basis points (bps) increase in loan spreads (compared to 185 bps median loan spread for the sample), and a probability of new loan origination lower by 0.5%. Numbers are similar when restricting the regression sample to low-uncertainty firms. Moreover, a one standard deviation increase in firms’ exposure to trade uncertainty via their relationship with exposed banks is associated with a decrease of the growth rate of the firms’ total debt and of their investment ratio in 2018–2019 by 2.4 and 2.7 ppts, respectively. These results are consistent with a credit supply contraction having a material adverse effect on exposed firms’ real outcomes.

A key empirical challenge in isolating the effects of trade uncertainty on credit supply is the fact that credit supply by banks and credit demand by firms may change simultaneously in response to changes in the trade environment. International trade is important for the banking sector as changes in firms’ foreign activities often shift their credit demand ([Amiti and Weinstein, 2011](#)). To address this issue, we exploit the granular nature of our data, at the bank-firm loan-level, with controls for firm $\times$ quarter fixed effects to absorb time-varying credit demand shifts for a given firm ([Khawaja and Mian, 2008](#); [Jiménez et al., 2020](#)). We also control for firm $\times$ bank fixed effects to account for time-invariant bank-specific loan demand for individual firms and for potential endogenous matching between banks and firms ([Chodorow-Reich, 2014](#); [Farinha et al., 2022](#); [Paravisini et al., 2023](#)). Placebo tests indicate that banks with different levels of exposure to trade uncertainty have similar lending patterns before the sample period, suggesting that unobservable bank characteristics do not explain our results. Throughout the analyses, we reinforce the importance of controlling for credit demand by presenting results on bank lending for two borrower samples: (i) all firms, and (ii) firms that are in low-uncertainty sectors and less likely to have strong endogenous shifts in

credit demand.<sup>5</sup>

We conduct additional tests to increase confidence in the interpretation of our results. First, we present evidence to allay the potential concern that our results are driven by the effects of the Trade War on loan returns (a first-moment effect) instead of the uncertainty regarding loan returns (a second-moment effect). Specifically, we show that the results are invariant to controlling for bank exposure to changes in actual trade policy (that is, the loan share to tariffs-hit sectors).

Second, results do not change when we additionally control for (a) bank exposure to other sources of uncertainty, such as political uncertainty in sectors other than trade; or for (b) bank exposure to changes in overall sentiment. Results are further robust to alternative potential explanations for our baseline findings, including the possibility that changes in macroeconomic conditions—such as fluctuations in the value of the U.S. dollar and in commodity prices—may correlate with the trade environment and affect banks’ lending decisions during the sample period. Our main findings are also invariant to controlling for bank cyclicalities, for bank exposures to tradable-goods producing sectors and to firms integrated in global value chains (arguably more exposed to exchange rate fluctuations), or when dropping oil companies from the sample (as the oil sector experienced a protracted credit contraction starting in 2015).

Third, additional results and alternative methodological choices further support our baseline findings. We show our results are not limited to the standard terms of loan contracts—volumes, spreads, and maturities—but also extend to other margins, with more exposed banks consistently tightening collateral requirements on loans to all borrowers more than other banks. Finally, the baseline findings are invariant to specification changes such as (a) including no fixed effects; (b) including loan-type $\times$ quarter and firm $\times$ loan-type $\times$ quarter fixed effects for trade finance and other loans; (c) using a weighted-least-squares estimation that accounts for variations in the precision of sectoral estimates of trade uncertainty; and (d) varying the period of analysis to allow for potential anticipation effects of the Trade War.

**Related literature** Our paper contributes to several strands of literature. First, we contribute to the literature on the real and financial effects of uncertainty (Rogers et al., 2024; Kaviani et al., 2020; Berger et al., 2020; Husted et al., 2020; Baker et al., 2016; Buch et al., 2015; Bloom, 2014).

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<sup>5</sup>In addition, we show that credit demand, as reflected in credit line utilization rates, actually goes up during the Trade War for firms in high-uncertainty sectors.

Global banks play an important role in the international transmission of financial stresses through lending and liquidity flows ([Amiti and Weinstein, 2018b](#); [De Haas and Van Horen, 2013](#); [Schnabl, 2012](#)). Some papers document consequences of uncertainty for bank lending ([Crozet et al., 2022](#); [Jasova et al., 2021](#); [Wu and Suardi, 2021](#); [Soto, 2021](#); [Alessandri and Bottero, 2020](#); [Valencia, 2017](#); [Bordo et al., 2016](#)), while others relate uncertainty to global liquidity or capital flows ([Avdjiev et al., 2020](#); [Kalemli-Özcan and Kwak, 2020](#); [Rey, 2015](#)). The literature emphasizes different reasons why aggregate risk conditions may affect bank credit, including through banks’ value-at-risk constraints and leverage ([Bruno and Shin, 2015](#)). Relative to this strand of literature, we focus on a specific type of uncertainty—around the trade environment—and its implications for the activities of banks that support international trade and hence the integration of trade and finance. Trade uncertainty differs from aggregate uncertainty because of its sectoral and geographic specificity, which allows us to delve deeper into the mechanisms at work.

Second, existing studies provide evidence that banks facilitating international trade amplify the effects of first-order balance sheet shocks on firms and households ([Paravisini et al., 2023](#); [Niepmann and Schmidt-Eisenlohr, 2017a,b](#); [Niepmann, 2015](#); [Michalski and Ors, 2012](#); [Amiti and Weinstein, 2011](#)). Our focus is instead on (a) the directional effect from trade to banks and (b) the effect of an uncertainty shock, both of which have received little attention. [Federico et al. \(2023a\)](#) document that policy actions associated with China’s accession to the World Trade Organization in 2001 had sizeable effects on bank loan supply to Italian firms. The authors find that endogenous financial frictions arise as a result of the trade shock’s negative effects on bank loan portfolios. [Hankins et al. \(2022\)](#) examine the effects of metal and steel tariffs enacted in 2018 on the supply of auto loans by U.S. finance companies and document negative spillover effects of these policies on consumer credit. Whereas we share with these papers a focus on the effects of trade policies on financial intermediaries’ lending decisions, our contribution emphasizes the effects of uncertainty around trade policies in the absence of a realized balance sheet shock.

Finally, our work builds on the insights of a growing literature on the economic effects of trade wars, which has a particular emphasis on U.S.-China trade relations. Evidence has been building on the real effects of the 2018–2019 tariff changes ([Fajgelbaum et al., 2023](#); [Caldara et al., 2020](#); [Novy and Taylor, 2020](#); [Handley and Limao, 2017](#)) and supply chain disruptions ([Grossman et al., 2024](#); [Amiti et al., 2019](#); [Huang et al., 2019](#); [Schiller, 2017](#), see [Antràs and Chor \(2022\)](#) for a survey).

Research documents almost complete pass-through of the tariff burden to U.S. prices ([Cavallo et al., 2021](#); [Amiti et al., 2019](#)) and adverse effects on consumption ([Vaughn, 2019](#)), investment ([Amiti et al., 2020](#)), and employment ([Flaaten and Pierce, 2019](#)). Our results emphasize that the effects of trade uncertainty on the real economy can be amplified through the banking sector, even in the absence of bank balance sheet losses, and are above and beyond those of the applied policy change.

## 2 Data and Bank Exposure to Trade Uncertainty

### 2.1 The U.S. “Credit Register”

Our empirical tests require representative and detailed information on the terms of commercial loans for lenders and borrowers. To this end, we rely on micro-level bank data akin to a credit register. Our main data source is the FR Y-14Q H1 “Wholesale credit schedule” (see [here](#) for more details). These data are collected quarterly from U.S. and foreign Bank Holding Companies (henceforth BHCs or ‘banks’ for simplicity) as part of the annual Dodd-Frank Stress Tests. As banking organizations with assets above \$50 billion were required to report these schedules during our sample period, these data cover the near-universe of commercial loans from large U.S. banks, which account for three-quarters of outstanding loan balances ([Favara et al., 2021](#)) and close to 90% of total banking sector assets ([Frame et al., 2023](#)). The reporting panel of banks fluctuates between 30 and 35 banks between 2016:Q1 and 2019:Q4.

The FR Y-14Q data set contains loan-level information on commercial and industrial loans (of minimum size \$1 million) to domestic borrowers. We use information on the value of loans outstanding to non-financial firms (firms in the utilities and financial sectors are excluded from the sample). We observe other characteristics of the loans, such as the type of loan (e.g., line of credit or term loan) and loan purpose (e.g., trade finance loan, etc.), interest rates, maturity, collateral requirements (whether the loan is secured), and collateral type (fixed assets and real estate, cash, accounts receivables and inventory, blanket liens). 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. Borrower-specific probability of default is derived from internal risk ratings-based models approved by supervisors. In addition, banks report a wide range of annual borrower characteristics such as total assets, profitability, cash holdings, tangibility, sales revenue, and total debt. The vast



majority of the bank borrowers in the data set, which account for 64% of non-financial business debt liabilities and 80% of U.S. output (Caglio et al., 2021), are privately-held firms. We merge the loan-level data with quarterly bank balance sheet and income statement items for each bank from form FR Y-9C.

Descriptive statistics for the loans, banks, and firms in our main regression sample are shown in Table 1. The median loan in our sample has a size of \$10 million and a spread of 185 bps (over the prime bank rate or LIBOR). Median loan growth across bank-firm pairs in the regression sample, computed relative to the start of the sample period (2016:Q1), is 0% (average growth is -23% for multi-lender firms and 1.1% for single-lender firms). In aggregate bank balance sheet data, average C&I loan growth at the 39 largest BHCs was 3.1% during 2016:Q1-2019:Q4. Median remaining time to maturity is 2.5 years, 13.4% of loans are demandable (with no specified maturity), and 7.2% of loans are new originations. Almost 60% of observations are credit lines and 2.4% are trade finance loans. There is significant variation in bank capital as measured by the ratio of common equity to total assets, which has an average of 11.5%. Close to 70% of firms belong to low-uncertainty sectors and 10% are publicly-traded.

## 2.2 Bank Exposure to Trade Uncertainty

A key element of our analysis is the measure of bank exposure to trade uncertainty. Construction of this variable proceeds in three steps. First, we use estimates of firm-level trade risk and uncertainty for U.S. firms from Hassan et al. (2019) to obtain trade uncertainty measures that vary at the sector level. Second, we assign these sector-level uncertainty measures to borrowers in the credit register based on their sectoral classification. Third, we aggregate this information at the bank level using banks’ initial loan shares to firms across sectors.

Hassan et al. (2019) rely on textual analysis that extracts information on the frequency of terms concerning trade and uncertainty for publicly-listed firms. This approach leverages computational linguistics tools applied to the transcripts of quarterly earnings conference calls to construct measures of risks facing listed firms. Textual analysis allows the authors to calculate the share of earnings calls language that identifies risks associated with specific topics. Key for our analysis is one such topic—trade risk and uncertainty—that captures discussions related to international trade and potential risk and uncertainty jointly (e.g., the words “tariffs” and “uncertain” occurring in a

call). Uncertainty is a second moment characteristic, as represented by the range of top biagrams in this analysis.<sup>6</sup>

Figure 1 shows the evolution of this measure between 2014 and 2019. As seen in panel A, trade uncertainty spikes in 2018 and remains high through 2019. Moreover, as shown in panel B, trade uncertainty rises considerably more than other sectoral risks such as those classified as political, environmental, or economic.<sup>7</sup> Caldara et al. (2020) examine the evolution of trade policy uncertainty using newspaper coverage and earnings-calls-based measures (see Figure OA-2) and confirm a sharp increase in uncertainty after 2017, which they link to concerns about “supply chain disruptions” and “higher costs of raw materials” amid hikes in tariff rates. They also argue that the main source of risks in 2017, when trade uncertainty indexes increase notably for the first time, was related to changes in corporate tax policy, notably the 2017 border tax adjustment proposal. Combined with the fact that increases in tariffs by the United States on its major trading partners started in February 2018 and paused in December 2019 with the U.S.-China agreement on the Phase One deal, we settle on the period between 2018:Q1 and 2019:Q4 as the period of “heightened trade uncertainty” or Trade War for purposes of the analysis. 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.<sup>8</sup>

Firm-level indicators of trade uncertainty are available only for listed firms in the Hassan et al. (2019) data set, while the credit register covers a large set of both public and private firms. Therefore, in the first step we merge the uncertainty measures to the credit register *by sector*. We obtain average uncertainty at the 3-digit NAICS sector level as the average of firm-level uncertainty across firms in each sector.<sup>9</sup> For the imputation of average uncertainty from listed firms to all firms,

<sup>6</sup>The top biagrams 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.

<sup>7</sup>Figure OA-1 depicts trade uncertainty relative to overall, political, and nonpolitical sentiment and shows that while trade uncertainty rose materially during 2018–2019, increases in measures of sentiment were more muted.

<sup>8</sup>Our choice of Trade War period is also corroborated by the findings of Hassan et al. (2021), who use textual 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.

<sup>9</sup>For this aggregation we use sectoral classifications from S&P Compustat for the firms. We aggregate the firm-level uncertainty information at the 3-digit NAICS level and not a more granular level to have sufficient firms in each sector for the average to be reliable. We check that our results are robust to accounting for the sparse firm-level data in some sectors with a weighted least squares estimation in the Online Appendix.

we rely on recent evidence that listed firms’ equity valuations strongly predict economic activity at the industry 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 for each sector between 2016–2017 (before the Trade War) and 2018–2019 (during the Trade War). Firms in the manufacturing and transportation sectors account for a larger fraction of those that are most affected.<sup>10</sup>

Critical for our identification strategy is assessing whether the firms in sectors that were more affected by rising trade uncertainty had similar performance relative to firms that were in less affected sectors before the Trade War. To test this identifying assumption, we rank sectors by this measure and construct an indicator variable for those sectors above the 75<sup>th</sup> percentile of the distribution of change in trade uncertainty. We then classify firms in the top quartile sectors as “high-uncertainty” firms and test whether the sales growth of these firms differed systematically from that of other firms before 2018. The results of this “parallel trends” test are shown in Figure 2, where we find no statistically significant difference in the sales growth of firms in high- and low-uncertainty sectors in 2016 and 2017, but a significant difference in the years thereafter. This figure suggests that the performance of firms exposed to large increases in uncertainty was not different before the Trade War and therefore that their performance during the Trade War cannot be attributed to differential pre-existing trends.<sup>11</sup>

The second step to construct a measure of bank exposure to trade uncertainty involves merging the sectoral measures of trade uncertainty with banks’ initial loan exposures to individual sectors. The initial bank share of loans to firms in individual sectors is computed relative to total bank loans and is the average over 2014–2015. This average helps (a) to construct a pre-determined measure of bank exposure (before the start of the sample period) that is likely unrelated to economic conditions during the Trade War and (b) to avoid relying on a single year of data which may result in a noisy measure. Combining these two inputs yields a continuous measure of bank-level exposure to trade

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<sup>10</sup>Figure OA-3 reports the change in trade uncertainty across all sectors in our sample and Table OA-1 lists the most and least affected sectors.

<sup>11</sup>The net effects of tariffs on bank lending to particular sectors is ex-ante ambiguous, as firms within each sector can both import and export (Bernard et al., 2007).

uncertainty for bank-sector pair  $\{b, s\}$  defined as:

$$Bank\ Exposure_{b,s}^U = \sum_{s' \neq s} \omega_{bs',2014-15} \times \Delta Uncertainty_{s',2018-19/2016-17},$$

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  $\omega_{bs',2014-15}$  captures the share of the sum of loans to firms in sector  $s'$  in bank  $b$ 's loan portfolio and  $\Delta Uncertainty_{s',2018-19/2016-17}$  measures the change in trade uncertainty for sector  $s'$ .<sup>12</sup> In the cross-section of banks, the average and median bank loan exposures to trade uncertainty are positive, which means that the average bank has an initial loan portfolio that is tilted towards sectors facing higher trade uncertainty during the sample period (see [Table 1](#)).

It is important for our identification strategy to check if the bank exposure to trade uncertainty is correlated with bank characteristics that may influence lending decisions. The identifying assumption for unbiased estimation of the effect of bank exposure to trade uncertainty on credit is that this exposure is not systematically correlated with other bank-level shocks. That is, banks should not sort into certain sectors such that unobserved bank-level shocks are correlated to both a decline in credit supply and increases in uncertainty in those same sectors ([Borusyak et al., 2022](#)). To check this assumption, in [Table OA-2](#) we regress bank exposure to trade uncertainty on bank size, leverage, the share of core deposits in liabilities, and sectoral specialization. The regression are run in the yearly cross-sections of banks as well as in a panel that stacks the data across all the years in the sample period. We find that the bank exposure measure is unrelated to these characteristics, nevertheless, we include them as controls in the baseline specification.

### 3 Bank Responses to Different Types of Shocks

From the outset, it is important to distinguish a “standard” bank balance sheet shock that affects actual or expected returns to lending to a particular sector (a first-moment effect) from an uncertainty shock (a second-moment effect). Whereas the typical balance sheet shock unambiguously

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<sup>12</sup>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. \(2023a\)](#).

generates losses or gains to the bank’s balance sheet, an uncertainty shock by itself need not do so. Instead, uncertainty increases the dispersion of returns to lending and raises the prospect of future balance sheet gains or losses without those gains or losses necessarily materializing (we provide corroborating evidence on this point in the next section). As a result, it is likely that banks’ lending responses to a rise in uncertainty differ from those to changes in realized returns.

The literature shows that banks typically react to negative shocks in particular sectors by reducing their exposures to those sectors, with some reallocation of lending capacity across sectors taking place.<sup>13</sup> By contrast, increased trade uncertainty makes it difficult to assess the range and magnitude of loan returns and their effects on capital ratios, which may induce banks to curtail loan exposures more broadly across borrowers. Indeed, standard portfolio allocation models predict that an increase in volatility of asset payoffs leads to a reduction in the risky portfolio share (Markowitz, 1952).<sup>14</sup>

Corporate finance theory offers additional cues regarding the potential responses of banks to higher uncertainty. Studies of investment under uncertainty at non-financial firms highlight how the irreversible features of fixed asset purchases affect the timing of those investments in periods of uncertainty (Dixit and Pindyck, 1994; Caballero and Pindyck, 1992; Pindyck, 1991; Bernanke, 1983). These studies establish a negative link between uncertainty and investment, as firms tend to postpone investment until uncertainty about future conditions declines (Handley and Limao, 2015; Bloom, 2009; Bloom et al., 2007).

In a similar vein, banks may react to heightened uncertainty by adopting wait-and-see behaviors, for instance, by pulling back on lending and increasing their flexibility to modify loan agreements. Exposed banks may reduce loan amounts and increase spreads. Wait-and-see behaviors may additionally manifest in loan maturities. For instance, exposed banks may decide to reduce loan maturities to shorten the period between financial statement audits, which allows the bank to evaluate borrower creditworthiness more frequently. Finally, exposed banks may extend more demandable loans, which affords them increased flexibility of capital allocation because demand

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<sup>13</sup>This may not be the case for specialized banks with significant exposures to an adversely-affected sector. Such banks may instead choose to maintain their exposures to that sector to limit the possibility of widespread defaults and related balance sheet losses (Giannetti and Saidi, 2018), to preserve profitable relationships from which rents can be extracted during normal times (Bolton et al., 2016; Petersen and Rajan, 1995), and to preserve reputational capital (Ding, 2000; Boot et al., 1993).

<sup>14</sup>Our assumption that banks display some level of risk aversion follows results in the literature, such as Ratti (1980); Sealey (1980); Ho and Saunders (1981); Altunbas et al. (2017).

loans can be called back on a short notice.

Our research design is structured around three main conjectures. The first conjecture hypothesizes that, once we control for firm credit demand, banks that are more exposed to trade uncertainty will have behaviors similar to those observed in the investment-under-uncertainty literature:

**Conjecture 1:** *Consistent with real-options theory, exposed banks adopt a wait-and-see attitude in the face of rising uncertainty, reducing credit supply broadly across all borrowers (as opposed to a particular group of borrowers, such as those with high exposure to trade uncertainty).*

Delving into sources of bank heterogeneity in lending behaviors, credit supply adjustments could be associated with bank capital constraints. The transmission of uncertainty shocks to lending decisions may be driven by the external finance premium for banks (Bernanke, 2007). As uncertainty increases, banks with smaller capital ratios may additionally have an incentive to boost their capital buffers for precautionary reasons (Valencia, 2017). As raising capital is costly, these banks may become less willing to bear risks in the form of lending. This mechanism by which capital buffers can help banks self-insure against potential losses suggests stronger credit supply contractions for exposed banks with lower levels of capital. Concretely, we examine evidence for this channel within the following conjecture:

**Conjecture 2:** *Consistent with financial frictions, lower capitalized banks exposed to trade uncertainty contract lending by more than other banks.*

A final conjecture pertains to the real implications for the firms that borrow from exposed banks. This issue is especially relevant 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 bank-dependent borrowers (see, e.g., Slovin et al. (1993); Kang and Stulz (2000); Chava and Purnanandam (2011); Chodorow-Reich (2014); Schwert (2018)). Accordingly, we conjecture the following:

**Conjecture 3:** *Real outcomes are worse for firms that borrow from banks with higher exposures to trade uncertainty than for other firms.*

## 4 Main Results

This section presents the empirical specifications and results of the estimations testing the conjectures. The results first assess whether trade uncertainty affects the supply of bank credit to U.S. firms through a wait-and-see mechanism (Sections 4.1, 4.2, and 4.3). Then we test for heterogeneity in bank responses to trade uncertainty depending on financial frictions (Section 4.4) and we examine how banks may reallocate their assets when faced with increased trade uncertainty. Lastly, we present evidence of real effects for borrowing firms (Section 4.5).

### 4.1 Wait-and-see behaviors: Trade uncertainty and bank credit supply

We start by assessing whether banks adjust their lending activities consistent with a wait-and-see approach. It is difficult to directly test for this type of behavior, therefore we compile a portfolio of evidence in support of this channel using information on the intensive and extensive margins of lending.

**Specification** According to Conjecture 1, an increase in bank exposure to trade uncertainty reduces the supply of bank credit broadly across firms. We test this conjecture by estimating a difference-in-differences specification linking trade uncertainty to lending outcomes:

$$y_{b,i,s,t} = \beta_1 \text{Bank Exposure}_{b,s} \times \text{Post}_t + \beta_2 X_{b,t-1} + \beta_3 X_{b,t-1} \times \text{Post}_t + \gamma_{i,t} + \delta_{b,i} + e_{b,i,s,t}, \quad (1)$$

where the dependent variable  $y_{b,i,s,t}$  in the baseline regressions is defined as either the loan growth (the growth of loan commitments from bank  $b$  to firm  $i$  in sector  $s$  relative to the beginning of the sample period) or the corresponding loan spread. The sample period includes all loans between 2016:Q1 and 2019:Q4. We define  $\text{Post}_t$  as an indicator variable equal to one during 2018:Q1 through 2019:Q4, and zero during 2016:Q1 through 2017:Q4.  $\text{Bank Exposure}_{b,s}$  is our measure of bank exposure to trade uncertainty as defined in Section 2.2. The coefficient of interest is  $\beta_1$ . A negative value for  $\beta_1$  in the loan growth specification (and a positive one in the loan spread specification) would provide evidence supporting the conjecture. We examine this specification in the full sample of firms and separately for low-uncertainty firms.

Coefficients are estimated with Ordinary Least Squares (OLS) and standard errors are double

clustered by bank-firm and quarter. Specification (1) includes (a) firm $\times$ quarter fixed effects ( $\gamma_{i,t}$ ) that allow us to keep loan demand constant at the firm level over time, and hence examine the differential lending behavior of banks with varying degrees of exposure to uncertainty vis-à-vis a given firm in a given year and (b) firm $\times$ bank fixed effects ( $\delta_{b,i}$ ), which allow for the possibility that loan demand is specific to the bank-firm pair. This may be the case when banks specialize in certain types of credit (such as trade credit) or certain types of borrowers (such as large exporters)—see, e.g., Ivashina et al. (2021) and Paravisini et al. (2023). These fixed effects aim to allay concerns that the coefficient on bank exposure,  $\beta_1$ , captures the effects of firm-specific factors such as credit demand, as opposed to banks’ supply-side lending decisions.

Specifications include standard determinants of bank lending decisions ( $X_{b,t-1}$ ), such as (lagged) size (log-total assets), capital (common equity divided by total assets), and core deposits (in percent of total liabilities). Given that bank exposure to trade uncertainty may capture some form of lending specialization, we also include a bank specialization measure that identifies banks with outsized exposures to individual sectors.<sup>15</sup> All the control variables enter both in levels ( $X_{b,t-1}$ ) as well as interacted with the  $Post_t$  dummy variable ( $X_{b,t-1} \times Post_t$ ) to make sure that the  $\beta_1$  coefficient is not contaminated by bank size, capital, deposit funding, or specialization.

**Baseline: Intensive margin** Table 2 reports estimates based on specification (1) estimated for the full sample of borrowers and for low-uncertainty firms. In columns 1 and 2, the coefficient of interest on the difference-in-differences term  $Bank\ Exposure_{b,s} \times Post_t$  is negative and statistically significant, and shows that rising trade uncertainty is associated with lower loan growth for more exposed banks, both for the full sample of firms and for low-uncertainty firms. The coefficient magnitudes are economically sizeable. Using the coefficients in column 1, an increase in bank exposure to trade uncertainty by one standard deviation (0.25) is associated with an average decline in loan growth by between 2.6 and 2.8 ppts (relative to the median growth rate of loan commitments of 0% over the sample period).

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<sup>15</sup>We obtain this measure as follows. We start by calculating the shares of loans for each bank in our sample at end-2017 to individual sectors using the 3-digit NAICS classification. Then, we calculate the 75<sup>th</sup> percentile of that distribution plus 1.5 interquartile ranges. The bank specialization variable is defined as a dummy variable that takes a value of one for bank-sector observations for which the share exceeds that threshold—these are the banks “specialized” in that particular sector—and zero otherwise. As shown in Table OA-2, this measure is uncorrelated with bank exposure to trade uncertainty. Furthermore, our baseline results are virtually identical if we use the specialization measure computed as the average of 2014 and 2015 instead of the one for 2017.



The estimates in columns 3 and 4 of [Table 2](#) show that banks with higher exposure to trade uncertainty charge higher loan spreads than other banks. The coefficient estimates are statistically significant and economically meaningful. Using the coefficients in column 3, an increase in bank exposure to trade uncertainty by one standard deviation is associated with an average increase in lending spreads of 6.5 and 7.1 bps for all and low-uncertainty firms, respectively.<sup>16</sup> Although these changes are relatively small compared to the median spread in the sample (185 bps), the directional movement supports the conjecture that the supply of credit from banks exposed to trade uncertainty shifted inward.<sup>17</sup>

Overall, our baseline results suggest that trade uncertainty is associated with a broad contraction in credit supply across borrowers, highlighting the indiscriminate effect of uncertainty on bank lending behaviors, which stands in contrast with the more discriminate effects of standard bank balance sheet shocks. The Online Appendix presents several robustness checks on our baseline results, including alternative samples of firms, fixed effects, and estimation methods.

## 4.2 Parallel trends and threats to identification of an uncertainty effect

**Parallel trends** A key identifying assumption behind the unbiased estimation of  $\beta_1$  is that banks made similar lending decisions before the 2018–2019 period regardless of their exposure to sectors later affected by rising trade uncertainty. To test the validity of this assumption, we first explore the dynamic difference-in-differences effects in our baseline regressions. [Figure 3](#) 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 difference-in-differences term before the trade uncertainty shock are statistically indistinguishable from zero in most periods before the Trade War, suggesting a lack of anticipation effects and pre-shock lending adjustment by banks (either in volume or spreads of loans). By contrast, during 2018–2019 we observe a statistically significant contraction in loan volumes (panel A) and a rise in spreads (panel B), both

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<sup>16</sup>Furthermore, when we estimate the difference-in-differences  $Bank\ Exposure_{b,s} \times Post_t$  coefficient separately for the sample of high- and low-uncertainty borrowers, t-tests of equality of coefficients across subsamples indicate we fail to reject the null hypothesis of coefficient equality for both loan growth and loan spreads at conventional levels.

<sup>17</sup>The credit register data further allows us to explore whether exposed banks are more likely to tighten collateral requirements to hedge against potential loan losses. Repeating the baseline regressions with a dummy variable taking value one for secured loans (corresponding to about three-quarters of all loans in the sample) as the dependent variable, we find that, indeed, more exposed banks are more likely to require loan risk mitigants during the period of heightened trade uncertainty (see [Table OA-3](#)).

of which become stronger over time.<sup>18</sup>

We also test the validity of the parallel trends assumption with formal placebo tests. These tests are meant to ensure that bank exposure to trade uncertainty does not capture the effects of bank unobservables—if it did, then we would find patterns similar to our baseline results in previous periods. As shown in [Table OA-5](#), when we shift the sample period back by one or two years, we find no systematic association between bank exposure to trade uncertainty and lending outcomes. These findings reduce potential concerns that our baseline results capture the effects of unobserved bank characteristics rather than those of trade uncertainty itself.

**First- versus second-moment effects** One concern might be that results are driven by the effect of the Trade War on realized returns to lending, instead of the uncertainty regarding returns to lending. We approach this issue with a few specifications that control for bank ex-ante exposure to changes in actual trade policy and captures expected returns. Specifically, we construct a measure of bank exposure to sectoral tariff changes at the end of 2017 as the share of loan commitments to firms in sectors that received tariffs during 2018–2019, sourced from [Flaen and Pierce \(2019\)](#). The binned scatterplot in [Figure OA-4](#) depicts a positive correlation between the exposure of banks to trade uncertainty and their exposure to sectors that experienced tariff changes during the Trade War.<sup>19</sup> We then include this additional measure in a horse-race regression with bank exposure to trade uncertainty, as shown in [Table 3](#), and find that the point estimates on trade uncertainty exposure barely change relative to the baseline results in [Table 2](#).

Delving deeper into the nature of the shock experienced by banks, we show that the baseline credit supply contraction is linked to expectations of a wider distribution of loan returns—a measured rise in uncertainty—as opposed to a realized bank balance sheet shock. To distinguish between these two possibilities, we test whether exposed banks adjust their internal risk assessments of borrower creditworthiness, which may be driven by worsening asset quality, higher asset volatility, or both. If there is no change in loan delinquencies, a rise in banks’ assessments of

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<sup>18</sup>We run an additional test to check for evidence that banks may have anticipated the Trade War and started adjusting their lending exposures ahead of time. To this end, we drop loan observations from 2017 from our regression sample and run the regressions by comparing lending outcomes during 2015–2016 versus 2018–2019. The estimates are reported in [Table OA-4](#) and show that the baseline results remain unchanged, suggesting that banks did not react in anticipation of the heightened uncertainty associated with the Trade War.

<sup>19</sup>Similarly, [Benguria et al. \(2022\)](#) show that textual measures of exposure to trade policy uncertainty are highly correlated with actual trade war exposures in the cross-section of non-financial firms.

borrower default risk can be explained by higher uncertainty.<sup>20</sup>

Results are reported in [Table 4](#). First, we examine the link between banks’ exposure to trade uncertainty and their forward-looking assessments of borrower creditworthiness based on borrower-level probabilities of default over a one-year horizon. Estimates in columns 1–2 suggest that banks with greater exposure to uncertainty assess their borrowers as having increased default risk, suggesting potential concerns of higher credit risk and future balance sheet losses. Nevertheless, as shown in columns 3–5 of [Table 4](#), aggregated bank balance sheet data does not reveal any evidence of a concurrent deterioration in loan performance nor of higher loan-loss reserves at exposed banks. Overall, the finding that exposed banks are more likely to downgrade the perceived creditworthiness of their borrowers but do not simultaneously experience worsening asset quality, provide additional support for the notion that the baseline findings are driven by an uncertainty (higher asset volatility) effect rather than a “standard” bank balance sheet shock.

### 4.3 Wait-and-see behaviors: Additional lending terms

**Loan maturities** Next, we assess whether exposed banks reduce the maturities of their loans, which could be a sign they are decreasing the “irreversibility” of loan commitments (alternatively, increasing the frequency with which they conduct financial audits for their borrowers and allow for the possibility of making loan modifications). In this case, the dependent variables are (a) the remaining time to maturity (the median maturity and time to maturity of loans in the credit register are 5 and 2.5 years, respectively) and (b) an indicator variable that categorizes loans as demandable. A demandable loan allows the lender to react swiftly to any concerns about firm performance and recall the loan. Once notified, the borrower must repay the principal and any associated interest. In these specifications, we follow [Li et al. \(2023\)](#) and include the following loan controls: the log of loan size (total loan commitment) and dummy variables for floating rate loans, secured loans, and loans with prepayment penalty.

[Table 5](#) reports the regression results. The estimates suggest that more exposed banks shorten the maturity of loans more than other banks, including for the low-uncertainty firms (columns 1–2), and that exposed banks are more likely to grant demandable loans, which increase lenders’

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<sup>20</sup>This follows from the Expected Default Frequency model of credit risk assessment followed by many banks, see [Treacy and Carey \(1998\)](#).

flexibility to recoup capital when borrowers show signs of stress (columns 5–6). Overall, these results corroborate Conjecture 1 and suggest that, as uncertainty rises, more exposed banks try to increase the flexibility of their lending by shortening the maturity of loan contracts and more frequently re-assessing the creditworthiness of their borrowers.

**Extensive margin** In Table 6 we report regression results for new loan originations based on equation (1) and we again display results for all and for low-uncertainty firms. Specifications in columns 1–2 vs. 3–4 differ on the construction of the dependent variable and the aggregation level of the data; specifically, in columns 1–2 we run regressions using loan-level data with a loan-origination dummy as the dependent variable, and thus capture a “pure” extensive margin effect. By contrast, in columns 3–4 we run regressions aggregating the data up to the bank-firm level and specifying the dependent variable as the share of new loan volume in total loans outstanding, thus capturing a mixture of extensive and intensive margin effects. Across specifications, the estimated coefficient on the difference-in-differences term is negative and statistically significant, implying that bank exposure to trade uncertainty affects the extensive margin of lending as well. In terms of economic relevance, a one standard deviation increase in banks’ exposure to trade uncertainty is associated with a probability of a new loan origination that is lower by approximately 0.5%. This effect contrasts with an unconditional probability of a new loan origination of about 5% over our sample period.

#### 4.4 Heterogeneous Effects across Banks due to Financial Constraints

**Specification** To examine the differential effects of trade uncertainty on lending behaviors that relates to bank financial frictions, we focus on two measures of bank capital: (a) common equity to assets (i.e., the simple leverage ratio) and (b) the Stressed Common Equity Tier 1 (CET1) ratio (the minimum CET1 ratio estimated under the “Supervisory Severely Adverse” scenario of the Dodd-Frank Act stress test). We test the conjecture with a modified version of specification (1):

$$\begin{aligned}
y_{b,i,s,t} = & \sum_{\tau=1,2} \beta_{\tau} \text{Bank Exposure}_{b,s} \times \text{Post}_t \times \text{Bank Type}_{b,\tau} \\
& + \beta_3 X_{b,t-1} + \beta_4 X_{b,t-1} \times \text{Post}_t + \gamma_{i,t} + \delta_{b,i} + e_{b,i,s,t},
\end{aligned} \tag{2}$$

where  $\tau = 1$  indicates a *Low-Capital Bank*,  $\tau = 2$  indicates a *High-Capital Bank*, and high-capital banks are those with a capital ratio above the 75<sup>th</sup> percentile of the cross-sectional distribution. Evidence of financial frictions would arise if the coefficient of interest  $\beta_1$  were greater than  $\beta_2$ . Additional evidence for this channel could come from shifts in banks' asset allocations conditional on their exposure to trade uncertainty. Heightened uncertainty could induce banks to reallocate capital to non-lending activities, to shrink their balance sheets, or a combination of strategies. If exposed banks anticipate capital constraints to become more binding, they may exhibit lower risk-appetite and change allocations in favor of safer securities rather than making risky commercial loans. To explore this possibility, we also examine changes in broad balance sheet components by degree of bank exposure to trade uncertainty in a bank-level panel for our sample period.

Table 7 provides the main tests for the financial frictions channel. In panel A we define the capital ratio as equity over assets, while panel B's measure is based on the banks' post-stress test CET1 capital ratio. Consistent with Conjecture 2, the estimates across all specifications indicate that lower-capital, more constrained banks reduce loan growth and increase loan spreads more than other banks. The results in columns 1–2 show that higher-capital banks do not reduce loan growth while lower-capital banks do. By contrast, exposed banks increase loan spreads regardless of capital level (columns 3–4). P-values of one-sided t-tests suggest that the credit contraction effects are relatively stronger for more constrained banks (and statistically significant at least at the 5% level of significance).

These estimates are economically meaningful and shed light on the role of capital in dampening the transmission of real shocks through the banking system. We estimate a version of the model in column 1 in panel A using the capital ratio in levels to assess loan growth at exposed banks at different capitalization levels. In particular, we compare the loan growth for a bank with median capital levels before the Trade War (11.6% at end-2017) with a bank with the median capital level before the GFC (8.5% at end-2007) at median exposure to trade uncertainty (1.77). After the increase in trade uncertainty, the average loan growth of the bank with post-GFC capital levels is almost 7 ppts higher than the bank capitalized at pre-GFC levels. This is a material difference compared to the median growth rate of lending over the sample period and highlights the role of higher capital ratios in enhancing the resilience of banks to uncertainty shocks like the Trade War.

Overall, these results suggest lower capacity and willingness to bear risk at lower-capital banks

that are exposed to trade uncertainty, which is consistent with a financial frictions channel underpinning our baseline effects.

**Portfolio re-balancing** In [Table OA-6](#) we examine asset portfolio re-balancing in the bank-quarter panel, for all banks (panel A) and separately for high vs. low capital banks (panels B and C). Regression results in panel A indicate no effect of bank exposure to trade uncertainty on total bank asset growth (column 1). However, loans as a percentage of total assets fall, which is consistent with the results for commercial loans in the credit register data (column 2). In addition, the share of securities in total assets increase at more exposed banks (with a statistically significant coefficient at 10%) while cash holdings remain unchanged (columns 3–4). These results suggest that banks respond to increases in trade uncertainty by shifting their asset-mix away from risky loans towards safer securities. Furthermore, the estimates in panels B and C indicate that these asset shifting patterns are stronger for lower-capital banks, across both definitions of capital ratio considered.

## 4.5 Real effects for firms

**Specification** Conjecture 3 posits that the credit supply impact of trade uncertainty will affect firms’ real outcomes. To test for this conjecture, we start by gathering firm financial data in a firm-year panel over 2016–2019 and construct a measure of firm exposure to trade uncertainty via the firm’s relationships with uncertainty-exposed banks. This is a continuous variable representing the average uncertainty exposure of a firm’s lenders, weighted by the share of each lender in total borrowing by that firm (at end-2014), defined as:

$$Firm\ Exposure_i^U = \sum_b \omega_{ib,2014} \times Bank\ Exposure_b^U, \quad (3)$$

where  $\omega_{ib,2014}$  is firm  $i$ ’s beginning-of-sample loan share from each bank  $b$ , and  $Exposure_b^U$  is bank  $b$ ’s total exposure to trade uncertainty (defined as the simple average across sectors of the bank-sector exposure from the baseline specifications). Then, we use a range of firm-level financial data

and the following specification to test for real effects:

$$y_{i,s,c,t} = \beta_1 Firm\ Exposure_i^U \times Post_t + \beta_2 X_{i,t-1} + \beta_3 X_{i,t-1} \times Post_t + \gamma_i + \delta_{s,c,t} + e_{i,s,c,t}, \quad (4)$$

and  $y_{i,s,c,t}$  refers to a range of firm-level outcomes including total debt growth and the investment ratio (capital expenditure divided by lagged fixed assets) for firm  $i$  in industry  $s$ , located in county  $c$  and in year  $t$ . We control for a wide range of (lagged) firm characteristics and risk attributes ( $X_{i,t-1}$ ). Following the literature (see, e.g., [Fazzari, Hubbard and Petersen, 1987](#); [Leary and Roberts, 2014](#); [Dinlersoz, Kalemli-Özcan, Hyatt and Penciakova, 2018](#)), we include firm size (log-assets), liquidity (cash and marketable securities as a share of assets), tangibility (tangible assets as a share of assets), interest coverage ratio (EBITDA/total interest expense), return on assets, and a dummy taking value one for firms with a speculative-grade internal risk rating. We also control for real sales growth, a proxy for the demand and growth opportunities facing each firm ([Whited and Wu, 2006](#)). Specifications include firm fixed effects ( $\gamma_i$ ) and industry $\times$ county $\times$ year fixed effects ( $\delta_{s,c,t}$ ) to absorb time-varying shifts in macroeconomic conditions affecting all firms in a given industry and county. Once again, specifications consider the sample of all firms, and also the sample of low-uncertainty firms. Values for  $\beta_1$  coefficient estimates that are negative and statistically significant would provide support for Conjecture 3. In addition to testing for the effect of trade uncertainty on firm outcomes, we interact the difference-in-differences term ( $Firm\ Exposure_i^U \times Post_t$ ) with two measures of bank dependence: (a) a dummy variable that captures whether a firm is private or public, anticipating stronger real effects for private firms to the extent that such firms are more bank-dependent and less able to secure financing in public debt markets, and (b) a dummy variable that takes value one for firms with above-median share of bank debt (approximated with the sum of utilized loan amounts from the banks in the FR Y-14Q sample).

**Results** Real effects results are presented in [Table 8](#). We run the regressions for all firms in columns 1–2 and low-uncertainty firm in columns 3–4. The estimates suggest that higher firm exposure to trade uncertainty via banks is associated with a contraction in firms’ total debt growth and investment rates. The estimated coefficients on the difference-in-differences term are statisti-

cally significant in all specifications except for total debt growth for low-uncertainty firms in column 3. The estimates suggest that firms in borrowing relationships with banks more exposed to trade uncertainty are unable to substitute reduced credit from those banks with other sources of financing, as their total debt growth declines. This credit contraction, in turn, has a material effect on their investment rates. In terms of economic magnitudes, the coefficient estimates in columns 1–2 indicate that an increase in firm exposure to trade uncertainty is associated with a reduction in the growth rate of debt and in the investment rate by 2.4 and 2.7 ppts, respectively. These are sizeable effects given that average debt growth and investment rate over the period are 5.5% and 17.3%.

Next, we examine whether bank-dependent firms are more adversely affected. We use two measures of bank dependence. First, we divide firms into those that are publicly-traded and those that are privately-held, with the latter group being significantly more bank-dependent than the former (see, e.g., [Caglio et al. \(2021\)](#)). Our assumption is that listed firms are more likely to tap alternative sources of finance, such as public debt markets, when their banks are unable to lend to them. The results in panel A of [Table 9](#) show that higher trade uncertainty has a significant dampening effect on private firms’ performance and no such effect for listed firms (the difference-in-differences coefficients are statistically significant for private firms in three of four specifications). Second, we define bank dependence as a high (above-median) share of bank debt in the firm’s total debt. The results for this measure are reported in panel B of [Table 9](#) and show a larger and statistically significant credit contraction at firms with higher bank dependence (in three of four specifications), corroborating the finding that bank-dependent firms are relatively more affected by trade uncertainty exposure through their banks.

Taken together, the results in this section are consistent with [Conjecture 3](#) and highlight that firms borrowing from exposed banks experience worse economic outcomes as trade uncertainty and tensions rise, which suggests that they cannot costlessly switch to alternative sources of finance. This effect is more pronounced for firms that are more reliant on banks.

## 5 Ruling Out Alternative Explanations

It is important to establish that our results are not driven by changes in macroeconomic conditions that may have occurred simultaneously with the rise in trade uncertainty during 2018–2019. Here



we entertain several alternative explanations for our results and supply evidence suggesting that these explanations are not the main driver of our findings.

**Trade uncertainty versus non-trade uncertainty** A possible concern is that the trade uncertainty measure captures risk factors that are unrelated to international trade developments but co-move to generate spurious results. Panel B of [Figure 1](#) suggests such a confounding effect is unlikely given the notable jump in trade uncertainty and not in other sectoral risks. Nevertheless, we run a horse-race regression where we add a measure capturing bank exposure to non-trade uncertainty (in interaction with the *Post* dummy) as an additional explanatory variable. This measure is computed in the same way as the baseline exposure to trade uncertainty, with the only difference that we obtain non-trade uncertainty measures at the sector level from firm-level risk indicators vis-à-vis all sectors other than trade. Other sectors include economic policy & budget, environment, institutions & political processes, health care, security & defense, tax policy, and technology & infrastructure. The results are reported in panel A of [Table OA-7](#), where the estimated coefficients on the difference-in-differences terms for the non-trade exposure measure is statistically insignificant, while our baseline coefficients remain statistically significant and with the expected sign.

**Trade uncertainty versus overall sentiment** We also report the results of a horse-race specification between bank exposure to trade uncertainty and bank exposure to changes in overall sentiment. The latter measure is a rough proxy of banks’ perceptions of future mean loan returns as captured in firms’ earnings call transcripts. In [Figure OA-1](#) we plot three measures of sentiment—overall, political and nonpolitical sentiment—over the sample period along with the aggregate trade risk measure. The plot shows that changes in sentiment during the Trade War were small relative to the rise in trade uncertainty, making it unlikely that it would confound our main results. To formally test whether sentiment matters, we construct a measure of bank exposure to overall sentiment similar to that calculated for trade uncertainty. As shown in panel B of [Table OA-7](#), the coefficients on this measure are statistically insignificant, while the coefficients on bank exposure to trade uncertainty are statistically significant and robust across specifications.

**Exchange rate movements** Next, we explore whether our results are driven by exchange rate fluctuations, which may co-move with trade uncertainty, given that the strength of the U.S. dollar

affects both banks’ asset quality and trade activities. The Bank of International Settlements (BIS) broad U.S. dollar index appreciated by 4.7% during the high-trade uncertainty period between January 1, 2018 and December 31, 2019.

Exchange rate fluctuations affect banks and firms through several traditional mechanisms. When the dollar appreciates, banks may pull back from lending if they expect repayment capacity to deteriorate among their borrowers, especially among those unhedged foreign borrowers with dollar-denominated debts. 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 growth prospects and profitability. In addition, several financial mechanisms can drive the link between the U.S. dollar and the provision of dollar credit. A stronger dollar is associated with tighter dollar credit conditions (Bruno and Shin, 2023; Niepmann and Schmidt-Eisenlohr, 2019), which implies that foreign exporters more reliant on dollar-funded bank credit, may experience a decline in credit access, higher loan spreads (Meisenzahl et al., 2021), and a slowdown in real activity. This, in turn, may dampen the growth of U.S. firms that rely on imported intermediate inputs for their production, which, in turn, can affect their credit risk as perceived by lenders.

To address the possibility that fluctuations in the value of the U.S. dollar explain our results, we conduct two tests. First, we examine whether our main results survive after we control for bank exposure to these alternative mechanisms. To this end, we construct an additional exposure measure representing, for each bank, the end-2017 share of outstanding loans to firms in tradable-goods producing sectors, which arguably are more exposed to U.S. dollar fluctuations than firms in non-tradable goods sectors. We follow Desai et al. (2008) and classify construction, retailers, transportation, and recreation as non-tradable goods producing sectors. We then interact this exposure uncertainty measure with the U.S. dollar broad exchange rate index and include it in the regression with our baseline trade exposure interaction. As shown in Table OA-8, estimates for this specification reveal that including this additional control variable does not affect the statistical and economic significance of the estimated coefficient on our key difference-in-differences term.

Second, we test whether banks differentially curtail their credit supply across credit lines (which are mainly used by firms as a source of liquidity insurance) versus term loans (typically 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, 2019). This channel predicts that our results should be stronger for term loans, which are more likely to be sold in the secondary market than credit lines (Gatev and Strahan, 2009). When we unpack the baseline difference-in-differences term by credit lines versus term loans, we find that credit lines are relatively more affected by an increase in trade uncertainty (see Table OA-9). For term loans, spreads increase at more exposed banks (columns 3–4), but loan growth does not change significantly neither in the full sample nor for low-uncertainty firms (columns 1–2). These results are therefore inconsistent with our baseline findings operating through a credit channel of dollar movements.

**Bank cyclicalities** An alternative explanation for our findings could be that bank exposure to trade uncertainty captures the degree of bank cyclicalities, that is, the sensitivity of a bank’s lending book 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 cyclicalities, 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 bank cyclicalities in interaction with the *Post* dummy: if anything, bank cyclicalities operates in the opposite direction of the uncertainty exposure, with more cyclical banks increasing loan volumes (and leaving spreads unchanged) during the Trade War (Table OA-10 panel A).

**Commodity prices** Following the sharp and sustained oil price decline that started in mid-2014, U.S. banks with more concentrated exposures in the oil sector experienced losses and cut down lending, especially to firms in the oil sector (Bidder et al., 2021). One might worry that our results pick up the effects of bank exposure to the oil sector, in particular those of the protracted credit crunch that followed the decline in oil prices. To alleviate this concern, we drop oil companies from the sample (broadly identified as those in the 2-digit NAICS “Mining, quarrying, and oil and gas extraction” sector). Removing oil companies from the sample leaves the results unchanged (Table OA-10 panel B).

**Credit demand** While our analysis focuses on understanding shifts in bank loan supply, it is equally important to determine how firms adjust credit demand in the face of uncertainty shocks.

To this end, we examine the credit utilization rate, defined as the ratio of credit utilized relative to credit committed. We run regressions in data aggregated at the firm-quarter level (where the dependent variable is the average utilization rate on credit lines of firms with multiple revolvers across banks). Regression estimates in [Table OA-11](#) indicate that credit line utilization rates are higher for high-uncertainty firms during the Trade War (that is, those firms in sectors with a change in average uncertainty between 2016–2017 and 2018–2019 above-75th percentile). The evidence thus suggests that firms most affected by the rise in trade uncertainty attempted to boost their liquidity positions by defensively drawing down bank credit lines. The rise in loan demand is thus inconsistent with the baseline evidence of declining loan growth and rising loan spreads at more exposed banks, increasing our confidence in a supply-side interpretation of the identified effects.

## 6 Conclusion

This paper shows that trade uncertainty affects U.S. banks’ domestic credit supply along several dimensions. Exploiting the large and unanticipated spike in trade uncertainty during the 2018–2019 Trade War, coupled with supervisory loan-level data for U.S. banks and firms, we document that banks with higher ex-ante exposure to sectors facing a greater increase in trade uncertainty pull back from lending, with negative real effects for bank-dependent firms. Our results highlight an important banking channel for the transmission of uncertainty shocks to the real economy, consistent with wait-and-see behaviors by banks. The results also emphasize that bank credit contraction can be another implication of protectionist trade policies that contribute to ongoing economic uncertainty. Our analysis suggests that a full accounting of the economic effects of trade disputes—realized or potential forms of deglobalization—should take into account the endogenous contractionary responses of the financial sector. Feedback effects between the financial sector and economic activity that originate with real sector shocks are a promising avenue for future research.

## References

- Alessandri, Piergiorgio and Margherita Bottero, “Bank lending in uncertain times,” *European Economic Review*, 2020, 128, 103503.
- Altunbas, Yener, Simone Manganelli, and David Marques-Ibanez, “Realized bank risk during the Great Recession,” *Journal of Financial Intermediation*, 2017, 32, 29–44.
- Amiti, Mary and David E. Weinstein, “Exports and Financial Shocks,” *Quarterly Journal of Economics*, 10 2011, 126 (4), 1841–1877.
- and David E Weinstein, “How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data,” *Journal of Political Economy*, 2018, 126 (2), 525–587.
- and —, “How Much Do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data,” *Journal of Political Economy*, 2018, 126 (2), 525–587.
- , Sang Hoon Kong, and David Weinstein, “The Effect of the U.S.-China Trade War on U.S. Investment,” May 2020. NBER Working Paper No. 27114.
- , Stephen J Redding, and David Weinstein, “The Impact of the 2018 Trade War on U.S. Prices and Welfare,” March 2019. NBER Working Paper No. 25672.
- Antràs, Pol and Davin Chor, “Chapter 5 - Global value chains,” in Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, eds., *Handbook of International Economics: International Trade, Volume 5*, Vol. 5 of *Handbook of International Economics*, Elsevier, 2022, pp. 297–376.
- Avdjiev, Stefan, Leonardo Gambacorta, Linda S Goldberg, and Stefano Schiaffi, “The shifting drivers of global liquidity,” *Journal of International Economics*, 2020, 125, 103324.
- Baker, Scott R., Nicholas Bloom, and Steven J. Davis, “Measuring Economic Policy Uncertainty,” *Quarterly Journal of Economics*, 07 2016, 131 (4), 1593–1636.
- Benguria, Felipe, Jaerim Choi, Deborah L Swenson, and Mingzhi Jimmy Xu, “Anxiety or pain? The impact of tariffs and uncertainty on Chinese firms in the trade war,” *Journal of International Economics*, 2022, 137, 103608.
- Berger, Allen N, Omrane Guedhami, Hugh H Kim, and Xinming Li, “Economic policy uncertainty and bank liquidity hoarding,” *Journal of Financial Intermediation*, 2020, p. 100893.
- Bernanke, Ben S., “Irreversibility, Uncertainty, and Cyclical Investment,” *Quarterly Journal of Economics*, 1983, 98 (1), 85–106.
- , “The financial accelerator and the credit channel,” 2007. Speech delivered at The Credit Channel of Monetary Policy in the Twenty-first Century Conference, Federal Reserve Bank of Atlanta, Atlanta, GA, June 15.
- Bernard, Andrew B., J. Bradford Jensen, Stephen Redding, and Peter K. Schott, “Firms in international trade,” *Journal of Economic Perspectives*, 2007, 21 (3), 105–130.
- Bidder, Rhys M, John R Krainer, and Adam Hale Shapiro, “De-leveraging or de-risking? How banks cope with loss,” *Review of Economic Dynamics*, 2021, 39, 100–127.
- Bloom, Nicholas, “The impact of uncertainty shocks,” *Econometrica*, 2009, 77 (3), 623–685.
- , “Fluctuations in uncertainty,” *Journal of Economic Perspectives*, 2014, 28 (2), 153–176.
- Bloom, Nick, Stephen Bond, and John Van Reenen, “Uncertainty and investment dynamics,” *Review of Economic Studies*, 2007, 74 (2), 391–415.
- Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo Emilio Mistrulli, “Relationship and transaction lending in a crisis,” *Review of Financial Studies*, 2016, 29 (10), 2643–2676.

- Boot, Arnoud WA, Stuart I Greenbaum, and Anjan V Thakor, "Reputation and discretion in financial contracting," *American Economic Review*, 1993, pp. 1165–1183.
- Bordo, Michael D, John V Duca, and Christoffer Koch, "Economic policy uncertainty and the credit channel: Aggregate and bank-level U.S. evidence over several decades," *Journal of Financial Stability*, 2016, 26, 90–106.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-experimental shift-share research designs," *The Review of Economic Studies*, 2022, 89 (1), 181–213.
- Bruno, Valentina and Hyun Song Shin, "Cross-border banking and global liquidity," *Review of Economic Studies*, 2015, 82 (2), 535–564.
- and —, "Dollar and exports," *Review of Financial Studies*, 2023, 36 (8), 2963–2996.
- Buch, Claudia M., Manuel Buchholz, and Lena Tonzer, "Uncertainty, Bank Lending, and Bank-Level Heterogeneity," *IMF Economic Review*, 2015, 63 (4), 919–954.
- Caballero, Ricardo J. and Robert S. Pindyck, "Uncertainty, investment, and industry evolution," *International Economic Review*, 1992, 37 (3), 641–662.
- Caglio, Cecilia, Matthew Darst, and Şebnem Kalemli-Özcan, "Collateral Heterogeneity and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms," 2021. NBER Working Paper No. 28685.
- Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo, "The economic effects of trade policy uncertainty," *Journal of Monetary Economics*, 2020, 109, 38–59.
- Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang, "Tariff Pass-Through at the Border and at the Store: Evidence from U.S. Trade Policy," *American Economic Review: Insights*, March 2021, 3 (1), 19–34.
- Chava, Sudheer and Amiyatosh Purnanandam, "The effect of banking crisis on bank-dependent borrowers," *Journal of Financial Economics*, 2011, 99 (1), 116–135.
- Chodorow-Reich, Gabriel, "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis," *Quarterly Journal of Economics*, 2014, 129 (1), 1–59.
- Cornett, Marcia Millon, Jamie John McNutt, Philip E Strahan, and Hassan Tehranian, "Liquidity risk management and credit supply in the financial crisis," *Journal of Financial Economics*, 2011, 101 (2), 297–312.
- Crozet, Matthieu, Banu Demir, and Beata Javorcik, "International trade and letters of credit: A double-edged sword in times of crises," *IMF Economic Review*, 2022, pp. 1–27.
- Desai, Mihir A, C Fritz Foley, and Kristin J Forbes, "Financial constraints and growth: Multinational and local firm responses to currency depreciations," *Review of Financial Studies*, 2008, 21 (6), 2857–2888.
- DeYoung, Robert, Anne Gron, Gokhan Torna, and Andrew Winton, "Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis," *Journal of Finance*, 2015, 70 (6), 2451–2488.
- Diñç, Serdar, "Bank reputation, bank commitment, and the effects of competition in credit markets," *Review of Financial Studies*, 2000, 13 (3), 781–812.
- Dinlersoz, Emin, Şebnem Kalemli-Özcan, Henry Hyatt, and Veronika Penciakova, "Leverage over the life cycle and implications for firm growth and shock responsiveness," 2018. NBER Working Paper No. 25226.
- Dixit, Avinash K. and Robert S. Pindyck, *Investment under Uncertainty*, Princeton University Press, 1994.

- Fajgelbaum, Pablo, Pinelopi K Goldberg, Patrick J Kennedy, Amit Khandelwal, and Daria Taglioni, “The U.S.-China trade war and global reallocations,” *American Economic Review: Insights (forthcoming)*, 2023.
- Farinha, Luisa, Sotirios Kokas, Serafeim Tsoukas, and Enrico Sette, “Real effects of imperfect bank-firm matching,” 2022. Bank of Portugal Working Paper 2022–10.
- Favara, Giovanni, Ivan Ivanov, and Marcelo Rezende, “GSIB surcharges and bank lending: Evidence from U.S. corporate loan data,” *Journal of Financial Economics*, 2021, *142* (3), 1426–1443.
- Fazzari, Steven, R Glenn Hubbard, and Bruce C Petersen, “Financing constraints and corporate investment,” *Brookings Papers on Economic Activity*, 1987, (1), 141–206.
- Federico, Stefano, Fadi Hassan, and Veronica Rappoport, “Trade shocks and credit reallocation,” *American Economic Review (forthcoming)*, 2023.
- , Giuseppe Marinelli, and Francesco Palazzo, “The 2014 Russia shock and its effects on Italian firms and banks,” 2023. NBER Working Paper No. 31171.
- Flaaen, Aaron and Justin Pierce, “Disentangling the Effects of the 2018-2019 Tariffs on a Globally Connected U.S. Manufacturing Sector,” May 2019. FEDS Note 2019–086.
- Flynn, Sean J and Andra Ghent, “Does Main Street Benefit from What Benefits Wall Street?,” *Journal of Financial and Quantitative Analysis*, 2022, pp. 1–37.
- Frame, W Scott, Ping McLemore, and Atanas Mihov, “Haste makes waste: Banking organization growth and operational risk,” 2023. FRB Dallas Research Department Working Paper Series No. 2023.
- Froot, Kenneth A and Jeremy C Stein, “Risk management, capital budgeting, and capital structure policy for financial institutions: An integrated approach,” *Journal of Financial Economics*, 1998, *47* (1), 55–82.
- Galaasen, Sigurd, Rumstam Jamilov, Ragnar Juelsrud, and Helene Rey, “Granular Credit Risk,” December 2021. NBER Working Paper No. 27994.
- Gatev, Evan and Philip E Strahan, “Liquidity risk and syndicate structure,” *Journal of Financial Economics*, 2009, *93* (3), 490–504.
- Giannetti, Mariassunta and Farzad Saidi, “Shock Propagation and Banking Structure,” *Review of Financial Studies*, 12 2018, *32* (7), 2499–2540.
- and Luc Laeven, “The flight home effect: Evidence from the syndicated loan market during financial crises,” *Journal of Financial Economics*, 2012, *104* (1), 23–43.
- Gilje, Erik P, Elena Loutskina, and Philip E Strahan, “Exporting liquidity: Branch banking and financial integration,” *Journal of Finance*, 2016, *71* (3), 1159–1184.
- Grossman, Gene M, Elhanan Helpman, and Stephen J Redding, “When tariffs disrupt global supply chains,” *American Economic Review*, 2024, *114* (4), 988–1029.
- Haas, Ralph De and Neeltje Van Horen, “Running for the exit? International bank lending during a financial crisis,” *Review of Financial Studies*, 2013, *26* (1), 244–285.
- Handley, Kyle and Nuno Limao, “Trade and investment under policy uncertainty: Theory and firm evidence,” *American Economic Journal: Economic Policy*, 2015, *7* (4), 189–222.
- and —, “Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States,” *American Economic Review*, September 2017, *107* (9), 2731–83.
- Hankins, Kristine, Watson, Morteza Momeni Shahraki, and David Sovich, “Does Trade Policy Affect Consumer Credit? The Role of Captive Finance Lenders,” *University of Kentucky (Department of Finance)*, 2022.

- Hassan, Tarek A, Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, “Firm-Level Political Risk: Measurement and Effects,” *Quarterly Journal of Economics*, 08 2019, 134 (4), 2135–2202.
- Hassan, Tarek Alexander, Jesse Schreger, Markus Schwedeler, and Ahmed Tahoun, “Sources and transmission of country risk,” *Review of Economic Studies* (forthcoming), 2021.
- , Stephan Hollander, Laurence van Lent, and Ahmed Tahoun, “The Global Impact of Brexit Uncertainty,” January 2020. NBER Working Paper No. 26609.
- , —, —, Markus Schwedeler, and Ahmed Tahoun, “Firm-Level Exposure to Epidemic Diseases: COVID-19, SARS, and H1N1,” April 2020. NBER Working Paper No. 26971.
- Ho, Thomas SY and Anthony Saunders, “The determinants of bank interest margins: Theory and empirical evidence,” *Journal of Financial and Quantitative analysis*, 1981, 16 (4), 581–600.
- Holmstrom, Bengt and Jean Tirole, “Financial intermediation, loanable funds, and the real sector,” *Quarterly Journal of economics*, 1997, 112 (3), 663–691.
- Huang, Yi, Chen Lin, Sibio Liu, and Heiwai Tang, “Trade networks and firm value: Evidence from the U.S.-China trade war,” 2019. Available at SSRN 3504602.
- Husted, Lucas, John Rogers, and Bo Sun, “Monetary policy uncertainty,” *Journal of Monetary Economics*, 2020, 115, 20–36.
- Ivashina, Victoria and David Scharfstein, “Bank lending during the financial crisis of 2008,” *Journal of Financial economics*, 2010, 97 (3), 319–338.
- , Luc Laeven, and Enrique Moral-Benito, “Loan types and the bank lending channel,” *Journal of Monetary Economics*, 2021.
- Iyer, Rajkamal, José-Luis Peydró, Samuel da Rocha-Lopes, and Antoinette Schoar, “Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis,” *The Review of Financial Studies*, 2014, 27 (1), 347–372.
- Jasova, Martina, Caterina Mendicino, and Dominik Supera, “Policy uncertainty, lender of last resort and the real economy,” *Journal of Monetary Economics*, 2021, 118, 381–398.
- Jiménez, Gabriel, Atif Mian, José-Luis Peydró, and Jesús Saurina, “The real effects of the bank lending channel,” *Journal of Monetary Economics*, 2020, 115, 162–179.
- Kalemli-Özcan, Şebnem and Jun Hee Kwak, “Capital flows and leverage,” *Annual Review of Economics*, 2020, 12, 833–846.
- Kang, Jun-Koo and Rene M Stulz, “Do banking shocks affect borrowing firm performance? An analysis of the Japanese experience,” *The Journal of Business*, 2000, 73 (1), 1–23.
- Kaviani, Mahsa S, Lawrence Kryzanowski, Hosein Maleki, and Pavel Savor, “Policy uncertainty and corporate credit spreads,” *Journal of Financial Economics*, 2020, 138 (3), 838–865.
- Khwaja, Asim Ijaz and Atif Mian, “Tracing the impact of bank liquidity shocks: Evidence from an emerging market,” *American Economic Review*, 2008, 98 (4), 1413–1442.
- Leary, Mark T and Michael R Roberts, “Do peer firms affect corporate financial policy?,” *Journal of Finance*, 2014, 69 (1), 139–178.
- Li, Lei, Elena Loutskina, and Philip E Strahan, “Deposit market power, funding stability and long-term credit,” *Journal of Monetary Economics*, 2023.
- Loughran, Tim and Bill McDonald, “When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks,” *Journal of Finance*, 2011, 66 (1), 35–65.
- Markowitz, Harry, “The utility of wealth,” *Journal of Political Economy*, 1952, 60 (2), 151–158.



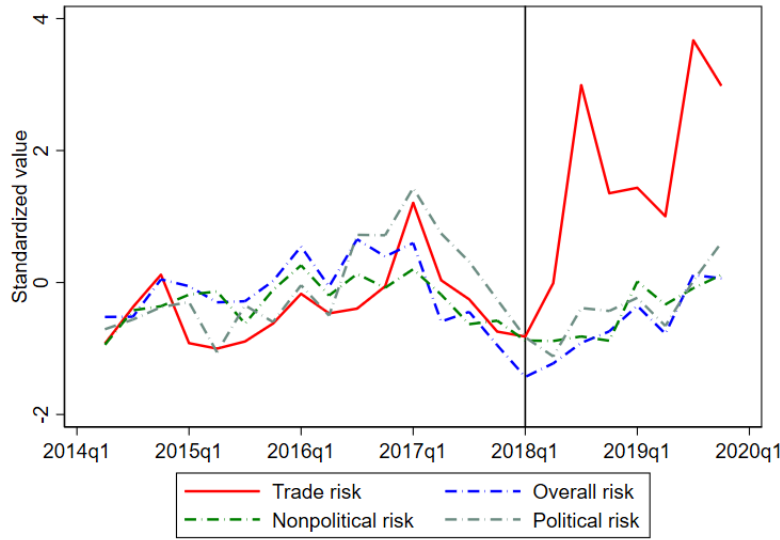
- Mayordomo, Sergio and Omar Rachedi, “The China Syndrome Affects Banks: The Credit Supply Channel of Foreign Import Competition,” *Journal of Financial and Quantitative Analysis*, 2022, 57 (8), 3114–3144.
- Meisenzahl, Ralf, Friederike Niepmann, and Tim Schmidt-Eisenlohr, “The dollar and corporate borrowing costs,” *International Finance Discussion Paper*, 2021, (1312).
- Michalski, Tomasz and Evren Ors, “(Interstate) Banking and (interstate) trade: Does real integration follow financial integration?,” *Journal of Financial Economics*, 2012, 104 (1), 89–117.
- Niepmann, Friederike, “Banking across borders,” *Journal of International Economics*, 2015, 96 (2), 244–265.
- and Tim Schmidt-Eisenlohr, “International trade, risk and the role of banks,” *Journal of International Economics*, 2017, 107, 111–126.
- and —, “No guarantees, no trade: How banks affect export patterns,” *Journal of International Economics*, 2017, 108, 338–350.
- and —, “Institutional investors, the dollar, and U.S. credit conditions,” *Journal of Financial Economics (forthcoming)*, 2019.
- Novy, Dennis and Alan M. Taylor, “Trade and Uncertainty,” *Review of Economics and Statistics*, 10 2020, 102 (4), 749–765.
- Ongena, Steven, Günseli Tümer-Alkan, and Natalja Von Westernhagen, “Do exposures to sagging real estate, subprime, or conduits abroad lead to contraction and flight to quality in bank lending at home?,” *Review of Finance*, 2018, 22 (4), 1335–1373.
- Paravisini, Daniel, Veronica Rappoport, and Philipp Schnabl, “Specialization in bank lending: Evidence from exporting firms,” *Journal of Finance*, 2023, (4), 2049–2085.
- Peek, Joe and Eric S Rosengren, “Collateral damage: Effects of the Japanese bank crisis on real activity in the United States,” *American Economic Review*, 2000, 90 (1), 30–45.
- Petersen, Mitchell A and Raghuram G Rajan, “The effect of credit market competition on lending relationships,” *Quarterly Journal of Economics*, 1995, 110 (2), 407–443.
- Pindyck, Robert S., “Irreversibility, Uncertainty, and Investment,” *Journal of Economic Literature*, September 1991, 29 (3), 1110–1148.
- Popov, Alexander and Neeltje Van Horen, “Exporting sovereign stress: Evidence from syndicated bank lending during the euro area sovereign debt crisis,” *Review of Finance*, 2015, 19 (5), 1825–1866.
- Puri, Manju, Jörg Rocholl, and Sascha Steffen, “Global retail lending in the aftermath of the US financial crisis: Distinguishing between supply and demand effects,” *Journal of Financial Economics*, 2011, 100 (3), 556–578.
- Ratti, Ronald A, “Bank attitude toward risk, implicit rates of interest, and the behavior of an index of risk aversion for commercial banks,” *Quarterly Journal of Economics*, 1980, 95 (2), 309–331.
- Rey, Hélène, “Dilemma not trilemma: The global financial cycle and monetary policy independence,” 2015. NBER Working Paper No. w21162.
- Rogers, John, Sun Bo, and Tony Sun, “U.S.-China Tension,” 2024. University of Virginia.
- Schiller, Christoph, “Financial Contagion in International Supply-Chain Networks,” February 2017. Mimeo, Arizona State University.
- Schnabl, Philipp, “The international transmission of bank liquidity shocks: Evidence from an emerging market,” *Journal of Finance*, 2012, 67 (3), 897–932.

- Schwert, Michael, “Bank capital and lending relationships,” *Journal of Finance*, 2018, 73 (2), 787–830.
- Sealey, C William, “Deposit rate-setting, risk aversion, and the theory of depository financial intermediaries,” *Journal of Finance*, 1980, 35 (5), 1139–1154.
- Slovin, Myron B, Marie E Sushka, and John A Polonchek, “The value of bank durability: Borrowers as bank stakeholders,” *Journal of Finance*, 1993, 48 (1), 247–266.
- Soto, Paul E., “Breaking the Word Bank: Measurement and Effects of Bank Level Uncertainty,” *Journal of Financial Services Research*, 2021, 59 (1), 1–45.
- Treacy, William F and Mark S Carey, “Credit risk rating at large U.S. banks,” *Federal Reserve Bulletin*, 1998, 84, 897.
- Valencia, Fabián, “Bank capital and uncertainty,” *Journal of Banking & Finance*, 2017, 81, 150–165.
- Waugh, Michael E., “The Consumption Response to Trade Shocks: Evidence from the U.S.-China Trade War,” 2019. NBER Working Paper No. 26353.
- Whited, Toni M and Guojun Wu, “Financial constraints risk,” *Review of Financial Studies*, 2006, 19 (2), 531–559.
- Wu, Wei-Shao and Sandy Suardi, “Economic Uncertainty and Bank Lending,” *Journal of Money, Credit and Banking*, 2021.

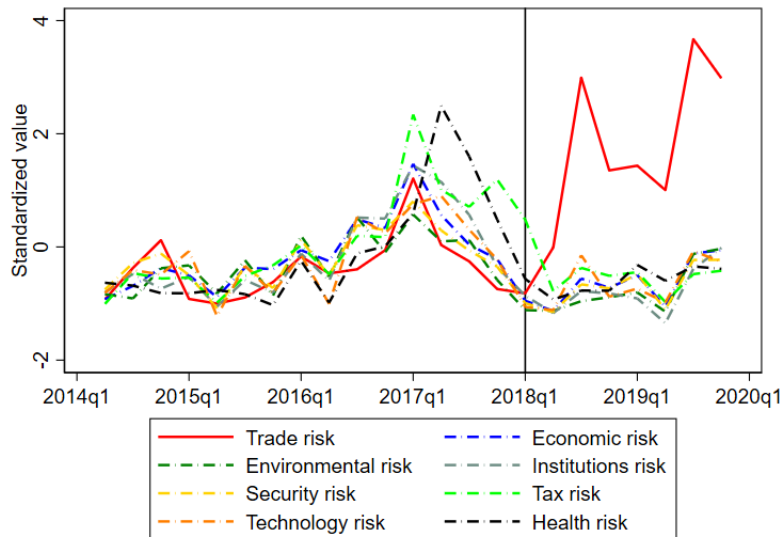
**Figure 1.** Trade and other uncertainty indexes

This figure depicts the evolution of the trade uncertainty index compared to aggregate indexes of overall, political, and nonpolitical risk (panel A) and sectoral risk (panel B). These measures are constructed using textual analysis of earnings call transcripts by listed firms and count the frequency of mentions of synonyms for “risk” or “uncertainty.” Individual risk indexes shown below are computed from firm-level data as quarterly averages across reporting U.S. firms and are standardized. Sources: [Hassan et al. \(2019, 2020a,b\)](#), and <https://sites.google.com/view/firmrisk>.

**A. Trade uncertainty index vs. aggregate uncertainty indexes**

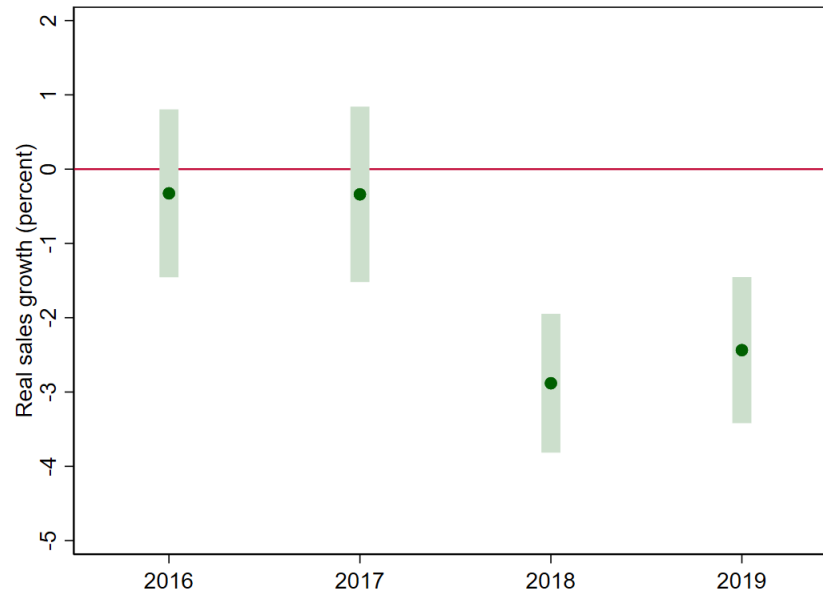


**B. Trade uncertainty index vs. sectoral uncertainty indexes**



**Figure 2.** Dynamic sales growth differential at high vs. low-uncertainty firms

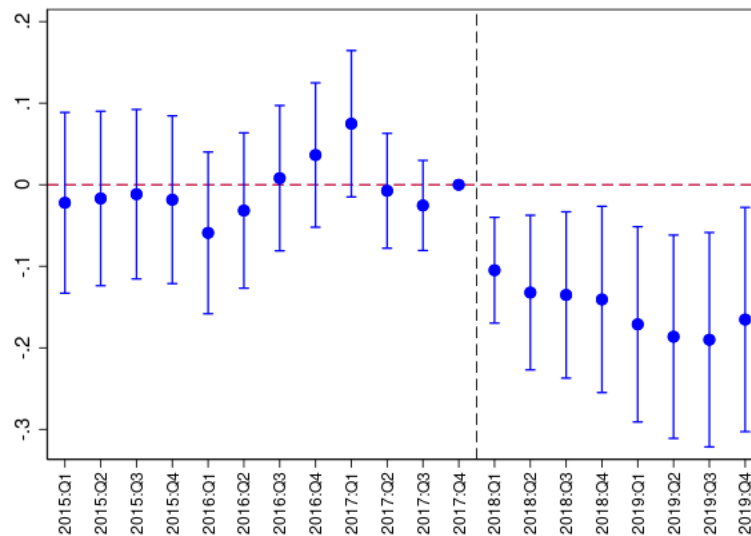
This figure shows the effects of firm exposure to trade uncertainty through its lenders on real sales growth during 2016-2019. The chart plots the estimated coefficients and the associated 99% confidence levels of a dynamic difference-in-differences model that regresses firm-level real sales growth on a dummy variable for high-uncertainty firms interacted with yearly dummies and firm characteristics (size, leverage, and cash holdings). Sources: FR Y-14Q and [Hassan et al. \(2019, 2020a,b\)](#).



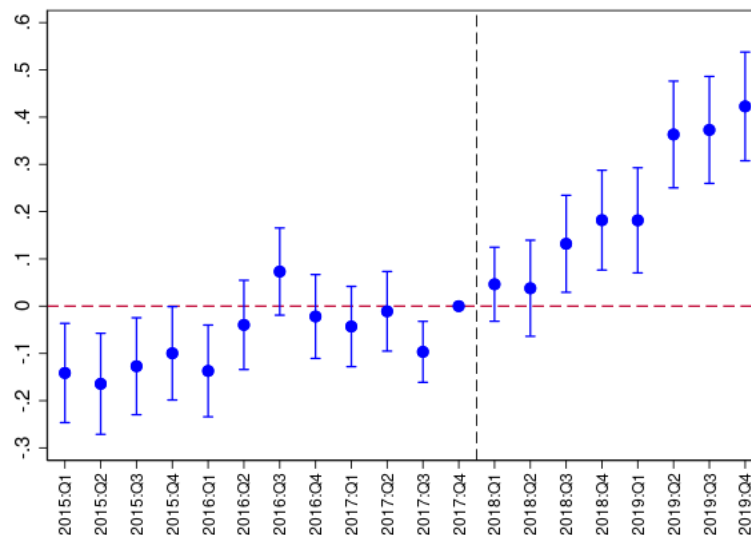
**Figure 3.** Dynamic difference-in-differences coefficient chart for intensive-margin lending outcomes at low-uncertainty firms

This figure shows the effects of bank exposure to trade uncertainty on loan growth (panel A) and loan spreads (panel B) for low-uncertainty firms during the sample period extended back by an additional year (that is, 2015:Q1–2019:Q4). The charts plot the estimated difference-in-differences coefficients and the associated 99% confidence levels of the dynamic variant of the specifications in columns 1 (loan growth) and column 3 (for spreads) in [Table 2](#) with interaction effects between bank exposure and quarterly dummies (with base period 2017:Q4).

### A. Loan growth



### B. Loan spreads



**Table 1.** Selected descriptive statistics

This table reports selected summary statistics for the loan-level regression sample and variables. Measures of bank exposure to trade uncertainty, tariffs and tradable-goods producing sectors are described in Section 2.2. Loan growth is computed as  $\log(\text{committed amount}_t / \text{committed amount}_{2016:Q4})$ . The regression sample at the loan level refers to U.S. BHCs with at least \$50 billion in assets that participate in Dodd-Frank stress tests and report to the FR Y-14Q before 2019; and domestic non-financial firms. Firms' share of bank debt refers to debt owed to Y-14Q reporting (stress-tested) banks. Sources: FR Y-14Q, U.S. Bureau of Economic Analysis (BEA), S&P Compustat, Flaaen and Pierce (2019), and Hassan et al. (2019, 2020a,b).

	N	Mean	St. Dev.	P25	P50	P75
<b>A. Bank characteristics</b>						
Exposure to trade uncertainty	318	1.782	0.248	1.639	1.772	1.915
Exposure to tariffs-hit sectors	312	0.338	0.104	0.280	0.333	0.429
Exposure to tradable-goods sectors	275	0.416	0.100	0.353	0.387	0.431
Exposure to non-trade uncertainty	318	-0.001	0.002	-0.003	-0.001	0.000
Exposure to overall sentiment	318	1.421	0.219	1.294	1.442	1.580
Size (log-assets)	318	19.435	1.035	18.681	19.148	19.924
Capital (common equity/assets)	318	11.549	2.054	10.102	11.433	13.111
Core deposits (% liabilities)	318	63.103	17.618	54.561	69.530	75.913
Specialization	318	0.381	0.486	0.000	0.000	1.000
1: High capital (common equity/assets)	318	0.390	0.489	0.000	0.000	1.000
1: High stress-test CET1 ratio	300	0.510	0.501	0.000	1.000	1.000
Cyclicality	318	1.179	1.158	0.661	1.100	1.431
<b>B. Firm characteristics</b>						
1: Firm in low-uncertainty sector	212973	0.698	0.459	0.000	1.000	1.000
1: Firm in tariffs-hit sector	216311	0.217	0.412	0.000	0.000	0.000
1: Firm in oil sector	216311	0.023	0.149	0.000	0.000	0.000
Total debt growth	18917	5.501	49.529	-13.706	0.000	18.643
Investment rate	18140	17.288	29.020	0.000	2.811	22.175
Firm exposure to uncertainty	18917	1.377	0.619	0.883	1.657	1.830
Size (log-assets)	18917	18.366	2.441	16.523	17.799	19.884
Liquidity (cash and mktb securities/assets)	18917	9.357	12.478	1.217	4.647	12.757
Tangibility (tangible assets/total assets)	18917	85.753	21.806	79.611	97.618	100.000
Interest coverage ratio (ICR)	18917	0.327	0.699	0.038	0.092	0.231
Return on assets (ROA)	18917	15.561	21.434	6.012	11.376	18.932
Sales growth	18917	11.530	36.631	-1.268	5.626	14.994
1: Firm is speculative-grade	18917	0.619	0.486	0.000	1.000	1.000
1: Firm is public	18917	0.108	0.311	0.000	0.000	0.000
1: Firm has high share of bank debt	17825	0.395	0.489	0.000	0.000	1.000
<b>C. Loan characteristics</b>						
Loan amount (USD million)	928768	28.291	71.978	2.770	10.000	31.250
Loan growth	928768	-0.230	0.937	-0.623	0.000	0.299
Loan spread (ppts)	540067	2.015	1.180	1.250	1.850	2.600
Time to maturity (years)	1095308	2.563	1.982	0.750	2.500	4.000
1: Loan is demandable	1095308	0.134	0.341	0.000	0.000	0.000
1: Loan is new origination	925630	0.072	0.258	0.000	0.000	0.000
1: Loan is secured	927367	0.774	0.418	1.000	1.000	1.000
Probability of default	868739	0.026	0.092	0.003	0.007	0.017
1: Loan is for trade financing	928768	0.024	0.152	0.000	0.000	0.000
1: Loan is a credit line	838702	0.574	0.494	0.000	1.000	1.000

**Table 2.** Wait-and-see behaviors: The intensive margin of 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 bank-firm-quarter loan-level and refer to outstanding loans to domestic borrowers (non-financial firms) during 2016:Q1–2019:Q4. Bank exposure to trade uncertainty is measured as the average of the difference in trade uncertainty across sectors (between 2016:Q1–2017:Q4 and 2018:Q1–2019:Q4), weighted by initial bank loans shares to those sectors (See [Section 2.2](#) for the construction of the variable). The dummy variable *Post* takes value of one for the period 2018:Q1–2019:Q4 and zero for the period 2016:Q1–2017:Q4. Bank controls include size (log-total assets), capital (common equity/total assets), deposits (core deposits/liabilities), and specialization, and enter in levels and interacted with *Post*. Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	<b>Loan growth</b>		<b>Loan spread</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure $\times$ Post	-0.102*** (0.030)	-0.111*** (0.036)	0.260*** (0.085)	0.283** (0.096)
Observations	925,465	658,123	481,152	337,955
$R^2$	0.342	0.350	0.856	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table 3.** Horse-race with bank exposure to the first-moment shock

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty in a horse-race with a measure of bank exposure to the first-moment effects, that is, actual changes in trade policy. This measure is computed as the average share of loan commitments to tariffs-hit sectors during 2014–2015. All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	Loan growth		Loan spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
Bank exposure to trade uncertainty $\times$ Post	-0.140*** (0.029)	-0.153*** (0.033)	0.233** (0.082)	0.262** (0.092)
Bank exposure to tariffs-hit sectors $\times$ Post	0.258*** (0.074)	0.271*** (0.088)	0.318** (0.110)	0.252** (0.111)
Observations	918,982	653,795	477,573	335,091
$R^2$	0.343	0.350	0.855	0.855
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y



**Table 4.** Banks' assessment of firm default risk versus realized loan losses

This table shows OLS estimates for a regression of banks' assessment of firm default risk and several metrics of asset quality on bank exposure to trade uncertainty. The dependent variable is the probability of default (PD) (columns 1–2); and loan loss reserve ratio, nonperforming loan ratio, and net charge-off ratio (columns 3–5). In columns 1–2 the data are at the bank-firm-quarter loan-level as in baseline [Table 2](#) and include all the firms in the dataset (that is, both single- and multi-lender firms) to capture banks' assessment of borrower risk across the entire loan portfolio. In columns 3–5 the data are at aggregate balance sheet data at the bank-quarter level over the baseline sample period 2016:Q1–2019:Q4. All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level in columns 1–2 and clustered at the bank level in columns 3–5. Significance: \*\*\* 1%, \*\*5%, and \*10%.

	(1)	(2)	(3)	(4)	(5)
Dependent variables:	<b>Probability of default</b>		<b>Loan loss reserves</b>	<b>Non- performing loans</b>	<b>Net charge-offs</b>
	<b>All firms</b>	<b>Low-uncertainty firms</b>			
Bank exposure $\times$ Post	0.010*** (0.003)	0.013*** (0.004)	-0.074 (0.110)	0.429 (0.277)	-0.129 (0.171)
Observations	1,432,240	998,525	452	452	452
$R^2$	0.012	0.013	0.989	0.947	0.968
Bank controls	Y	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y

**Table 5.** Wait-and-see behaviors: Loan maturities and demandable loans

This table shows OLS estimates for a regression of loan maturities on bank exposure to trade uncertainty. The dependent variable is the remaining time to maturity in quarters (columns 1–2) and a dummy variable for demandable loans in the extended dataset that includes such loans (columns 3–4). Demandable loans are only included in the analysis of loan maturities in columns 3–4 of this table. All specification details, sample period, and controls as in Table 2. Other loan controls include the log of loan size (total loan commitment) and dummy variables for floating rate loans, secured loans, and loans with prepayment penalty. Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

	(1)	(2)	(3)	(4)
	<b>Time to maturity (years)</b>		<b>Loan is demandable</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure $\times$ Post	-0.143*** (0.040)	-0.095** (0.039)	0.021** (0.009)	0.016* (0.008)
Observations	1,091,466	705,790	1,095,308	708,517
$R^2$	0.714	0.678	0.768	0.512
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Other loan controls	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y		

**Table 6.** Wait-and-see behaviors: The extensive margin of lending

This table shows OLS estimates for a regression of extensive margin of lending outcomes on bank exposure to trade uncertainty. The dependent variable is a dummy variable that takes value one for new loan originations in loan-level data and zero otherwise (panel A) or the share of new loans (volume weighted) in bank-firm-quarter level data (panel B). All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1) <b>Loan is new origination</b>	(2) <b>Loan is new origination</b>	(3) <b>Share of new loan originations (volume-weighted)</b>	(4) <b>Share of new loan originations (volume-weighted)</b>
	<b>A. Loan-level data</b>		<b>B. Bank-firm level data</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure $\times$ Post	-0.018*** (0.005)	-0.017** (0.008)	-0.017*** (0.005)	-0.019** (0.007)
Observations	925,630	658,255	346,388	246,891
$R^2$	0.581	0.588	0.668	0.678
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table 7.** Financial constraints: Role of bank capital

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty allowing for heterogeneous effects by bank capital. The measure of capital is common equity divided by total assets (at end-2017) in panel A and post stress-test CET1 capital ratio (defined as the minimum CET1 capital ratio estimated under the “Supervisory Severely Adverse” scenario of the Dodd-Frank Act stress test) in panel B. High-capital banks have capital ratios above the 75<sup>th</sup> percentile. All specification details, sample period, and controls as in Table 2. Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	Loan growth		Loan spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. Bank capital: Equity/Assets</b>				
Bank exposure $\times$ Post $\times$ Low-capital	-0.173*** (0.036)	-0.158*** (0.039)	0.337** (0.144)	0.367** (0.167)
Bank exposure $\times$ Post $\times$ High-capital capital	-0.011 (0.037)	-0.075 (0.046)	0.164*** (0.045)	0.172*** (0.041)
p-value t-test $H_a :  1  >  2 $	-	-	0.043	0.049
Observations	925,467	658,123	481,152	337,955
$R^2$	0.740	0.744	0.856	0.856
<b>B. Bank capital: Post-stress test CET1 ratio</b>				
Bank exposure $\times$ Post $\times$ Low-capital	-0.242*** (0.041)	-0.220*** (0.048)	0.332* (0.159)	0.367* (0.177)
Bank exposure $\times$ Post $\times$ High-capital capital	0.017 (0.033)	-0.033 (0.040)	0.188*** (0.049)	0.197*** (0.046)
p-value t-test $H_a :  1  >  2 $	-	-	0.034	0.064
Observations	886,460	629,384	458,023	320,494
$R^2$	0.742	0.746	0.856	0.857
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table 8.** Real effects of trade uncertainty through bank lending: Full sample

This table shows OLS estimates for a regression of firm-level total debt growth and investment ratio on firm exposure to trade uncertainty through its lenders. 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 at end-2014. The data are at the firm-year level over the period between 2016 and 2019. The dummy variable *Post* takes value one for the period 2019–2019 and zero for the period 2016–2017. Firm controls include size (log-assets), liquidity (cash and marketable securities/assets), tangibility (tangible assets as a share of total assets), interest coverage ratio (EBITDA/total interest expense), ROA (return on assets), real sales growth—all lagged one year—and a dummy variable taking value one for firms rated speculative-grade by their lender banks, and enter in levels and interacted with *Post*. Firm industry is 3-digit NAICS classification. Standard errors are clustered at the firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

	(1)	(2)	(3)	(4)
	Total debt growth		Investment rate	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
Firm exposure to trade uncertainty $\times$ Post	-0.038* (0.019)	-0.022 (0.023)	-0.044*** (0.010)	-0.053*** (0.011)
Observations	18,917	13,251	19,978	14,180
$R^2$	0.515	0.502	0.703	0.705
Firm controls	Y	Y	Y	Y
Firm controls $\times$ Post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry $\times$ County $\times$ Year FE	Y	Y	Y	Y

**Table 9.** Real effects of trade uncertainty through bank lending: Heterogeneity by dependence on bank debt

This table shows OLS estimates for a regression of firm-level total debt growth and investment rate on firm exposure to trade uncertainty through its lenders, allowing for heterogeneity by degree of dependence on bank debt. Dependent on bank debt is proxied by firm ownership (private/public) in panel A and by the share of bank debt (above/below median share of utilized loans from FR Y-14Q reporting banks in the firm's total debt) in panel B. 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 at end-2014. The data are at the firm-year level over the period between 2016 and 2019. The dummy variable *Post* takes value one for the period 2019–2019 and zero for the period 2016–2017. Firm controls include size (log-assets), liquidity (cash and marketable securities/assets), tangibility (tangible assets as a share of total assets), interest coverage ratio (EBITDA/total interest expense), ROA (return on assets), real sales growth—all lagged one year—and a dummy variable taking value one for firms rated below investment-grade by their lender banks, and enter in levels and interacted with *Post*. Firm industry is 3-digit NAICS classification. Standard errors are clustered at the firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

	(1)	(2)	(3)	(4)
	Total debt growth		Investment rate	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. Bank dependence: Private vs. public firms</b>				
Firm exposure × Private firm (1)	-0.038*	-0.021	-0.047***	-0.054***
	(0.020)	(0.023)	(0.010)	(0.012)
Firm exposure × Public firm (2)	-0.034	-0.007	-0.023	-0.051
	(0.057)	(0.068)	(0.026)	(0.032)
p-value t-test $H_a :  1  >  2 $	-	-	-	-
Observations	18,917	21,469	19,978	13,251
$R^2$	0.515	0.626	0.703	0.502
<b>B. Bank dependence: Share of bank debt</b>				
Firm exposure × Higher bank debt share (1)	-0.045**	-0.031	-0.058***	-0.070***
	(0.020)	(0.024)	(0.011)	(0.013)
Firm exposure × Lower bank debt share (2)	-0.032	-0.015	-0.047***	-0.055***
	(0.021)	(0.025)	(0.011)	(0.013)
p-value t-test $H_a :  1  >  2 $	-	-	0.071	0.032
Observations	18,917	13,251	17,865	12,609
$R^2$	0.515	0.502	0.707	0.709
Firm controls	Y	Y	Y	Y
Firm controls × Post	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Industry × County × Year FE	Y	Y	Y	Y

## ONLINE APPENDIX

### Trade Uncertainty and U.S. Bank Lending

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## A-I Appendix: Additional Robustness Checks

This section presents additional tests that validate the identification strategy and examine the robustness of our results to alternative methodological choices.

**Additional sample checks** We start by adjusting our regression sample to reflect a more restrictive notion of low-uncertainty firms that are even more removed from international trade activities than in the baseline. This approach allows us to strengthen the confidence that we identify spillovers to unaffected sectors across different definitions of “unaffected”. We restrict our sample in two dimensions: (i) by limiting it to firms in sectors with no tariff changes in the period of study, and (ii) by dropping not only high-uncertainty firms, but also the few remaining trade finance loans. Our results, shown in panel A of [Table OA-12](#), are robust to these adjustments. We then return to our baseline specifications and remove all fixed effects. As seen in panel B of [Table OA-12](#), we find no material changes to our main findings.

**More stringent (loan-type) fixed effects** A potential concern is that firms may have different types of loan relationships across banks (e.g., only trade finance loans with one bank and other kinds of loans with another). This possibility would limit the ability of firm $\times$ quarter fixed to absorb all the variation in credit due to changes in loan demand. To address this potential concern, we estimate our baseline specifications including loan-type $\times$ quarter fixed effects (panel A) and the even more stringent firm $\times$ loan-type $\times$ quarter fixed effects (panel B), where loan-type refers to (i) trade finance loans, (ii) loans secured by fixed assets and real estate, cash and marketable securities, or blanket liens (roughly capturing asset-based loans) and (iii) loans secured by accounts receivable and inventory (earnings-based loans). These loan categories are important to consider separately because credit dynamics following monetary and financial shocks can vary significantly across these loan types ([Ivashina et al., 2021](#)). Our baseline results, reported in [Table OA-13](#), remain unchanged.

**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 for which textual analysis is performed to measure uncertainty. To account for this issue, we estimate our baseline specifications using weighted-least squares 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 [Table OA-14](#) show that applying this weighting does not materially affect our main findings.

**Alternative measures of trade uncertainty** Our approach prompts the question of how the index of trade political risk and uncertainty from [Hassan et al. \(2019\)](#) compares with other prominent measures of trade policy uncertainty, such as that of [Caldara et al. \(2020\)](#). Thus, we check if our results hinge on our choice of constructing the baseline measure of bank exposure to trade policy uncertainty based on the [Hassan et al. \(2019\)](#) measures. The trade policy index of [Caldara et al. \(2020\)](#) is similar to that of [Hassan et al. \(2019\)](#) in that it uses similar linguistic libraries, including terms that refer to trade activities and trade policy, as well as uncertainty, risk, and potentiality. However, [Caldara et al. \(2020\)](#)’s index differs in two key dimensions. First, it uses news articles from global newspapers as a basis for the text analysis.<sup>21</sup> Second, it is more focused on measuring trade policy uncertainty, even though the [Hassan et al. \(2019\)](#) index uses policy-related keywords as well. As a result, the two indexes are highly correlated over the period of analysis (Figure OA-2), when trade uncertainty was largely driven by policies, and produce a similar sorting of firms and sectors into high versus low-uncertainty sectors. As seen in the bottom panel of Table OA-14, the results hold up using the [Caldara et al. \(2020\)](#) index: the coefficients on bank exposure to trade uncertainty are negative though imprecisely estimated for loan growth (columns 1-2) and positive and statistically significant for loan spreads (columns 3-4).

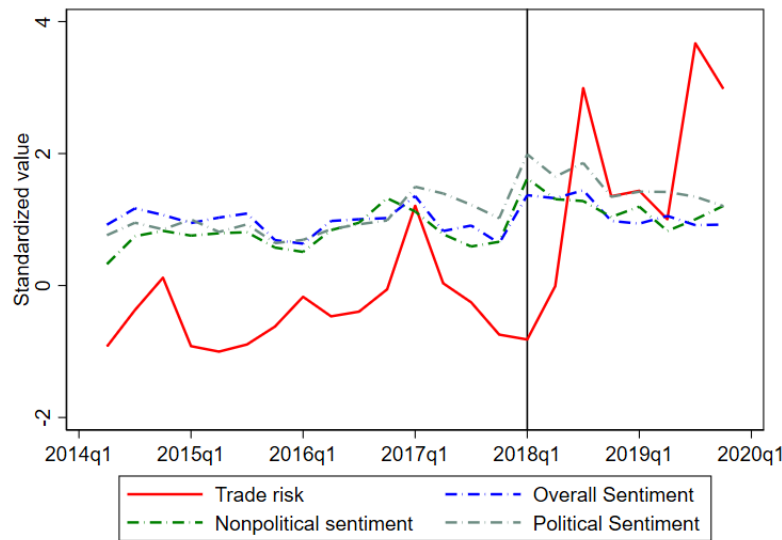
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<sup>21</sup>[Caldara et al. \(2020\)](#) additionally present a trade policy uncertainty index that uses transcripts from listed firms’ earnings calls and show that his index is highly correlated in the time series with their main news-based index.



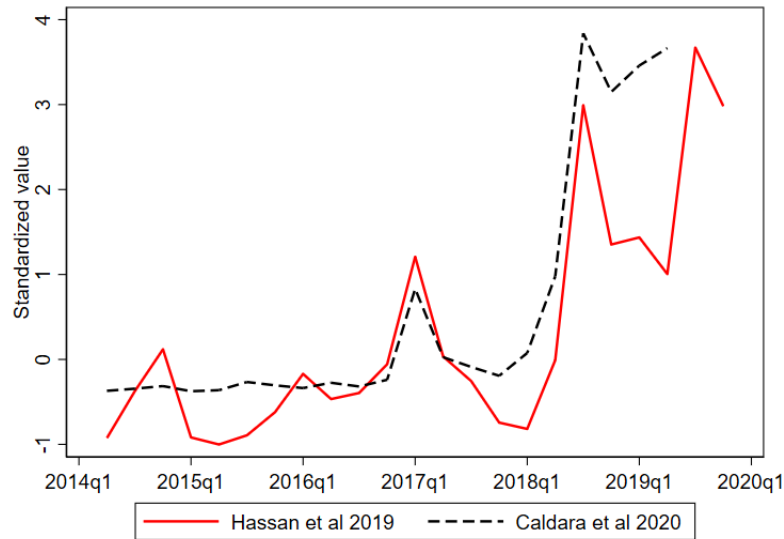
**Figure OA-1.** Trade uncertainty index vs. sentiment indexes

This figure depicts the evolution of the trade uncertainty index compared to aggregate indexes of overall, political and nonpolitical sentiment. The trade uncertainty index is described in [Section 2](#). The sentiment measures are constructed using textual analysis of earnings call transcripts by listed firms and count the frequency of mentions of positive words, deduct the frequency of mentions of negative words, and divide by the length of the transcript. Frequently-used positive and negative tone words are defined by include good, strong, great, loss, decline, and difficult, respectively (as in [Loughran and McDonald \(2011\)](#)). In the figure below, individual sentiment indexes are computed from firm-level data as quarterly averages across reporting U.S. firms and are standardized. Sources: [Hassan et al. \(2019, 2020a,b\)](#), and <https://sites.google.com/view/firmrisk>.



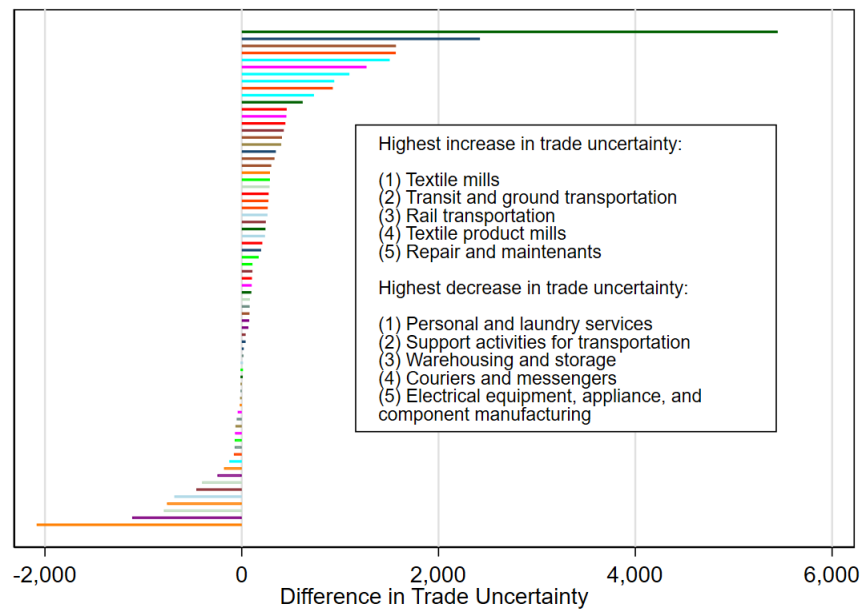
**Figure OA-2.** [Hassan et al. \(2019\)](#) vs [Caldara et al. \(2020\)](#) trade uncertainty indexes

This figure depicts the evolution of the trade uncertainty index from [Hassan et al. \(2019, 2020a,b\)](#) with that from [Caldara et al. \(2020\)](#). The first index is described in [Section 2](#). The second index is described in [Appendix A-I](#). Time-series for both indexes are obtained by taking the quarterly average of firm-level trade uncertainty indicators. Sources: [Hassan et al. \(2019, 2020a,b\)](#) and [Caldara et al. \(2020\)](#).



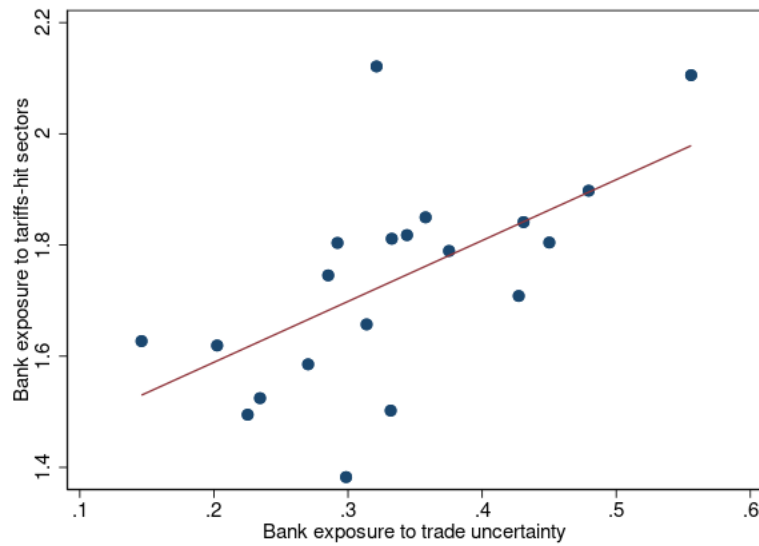
**Figure OA-3.** Average change in trade uncertainty by 3-digit NAICS sector

The figure depicts the average change in trade uncertainty between 2016-2017 and 2018-2019 by 3-digit NAICS sector. Uncertainty at the sector level is computed as average firm-level uncertainty, which in turn is based on textual analysis of transcripts from quarterly earnings calls of listed companies. The units of measurement for “Difference in trade uncertainty” is the frequency (number) of mentions of synonyms for risk or uncertainty, divided by the length of the transcript, and multiplied by 1,000. The text box lists the five sectors with the highest increases and decreases in trade uncertainty. The sector “Apparel manufacturing” (NAICS code 315) is omitted from the figure due to extreme value for uncertainty driven by earnings transcript of one firm. Sources: FR Y-14Q, [Hassan et al. \(2019, 2020a,b\)](#).



**Figure OA-4.** Bank exposure to trade uncertainty vs. tariffs-hit sectors and overall uncertainty

The figure depicts a binned scatterplot of bank exposure to trade uncertainty vs. bank exposure to tariffs-hit sectors, constructed as the average share of loan commitments to firms in tariffs-hit sectors over 2014–2015. In the cross-section of banks, this exposure and the baseline exposure to trade uncertainty have a correlation coefficient of 0.37. Sources: FR Y-14Q, [Hassan et al. \(2019, 2020a,b\)](#).



**Table OA-1.** Changes in trade uncertainty by sector

This table reports the sectors in the top 25<sup>th</sup> and bottom 25<sup>th</sup> percentiles of the distribution of changes in average trade uncertainty between 2016–2017 and 2018–2019. The units of measurement for “Change in trade uncertainty” is the frequency (number) of mentions of synonyms for risk or uncertainty, divided by the length of the transcript, and multiplied by 1,000. The sector “Apparel manufacturing” (NAICS code 315) is omitted from the table due to extreme value for uncertainty driven by earnings transcript of one firm. Sources: [Hassan et al. \(2019, 2020a,b\)](#).

Sector code	A. Largest increases in trade uncertainty	Change in trade uncertainty
313	Textile Mills	5447.8
485	Transit and Ground Passenger Transportation	2420.6
482	Rail Transportation	1567.7
314	Textile Product Mills	1565.6
811	Repair and Maintenance	1503.8
532	Rental and Leasing Services	1268.3
525	Funds, Trusts, and Other Financial Vehicles	1094.2
483	Water Transportation	940.3
331	Primary Metal Manufacturing	925.5
516	Broadcasting and Content Providers	734.2
333	Machinery Manufacturing	619.5
523	Securities, Commodity Contracts, and Other	457.2
445	Food and Beverage Retailers	454.0
519	Web Search Portals, Libraries, Archives, and Other Information Services	443.5
621	Ambulatory Health Care Services	427.2
112	Animal Production and Aquaculture	408.9
334	Computer and Electronic Product Manufacturing	401.3
<b>B. Largest decreases in uncertainty</b>		
812	Personal and Laundry Services	-1113.7
488	Support Activities for Transportation	-792.4
493	Warehousing and Storage	-760.0
492	Couriers and Messengers	-685.4
335	Electrical Equipment, Appliance, and Component Manufacturing	-462.2
236	Construction of Buildings	-404.0
524	Insurance Carriers and Related Activities	-247.6
531	Real Estate	-180.4
623	Nursing and Residential Care Facilities	-126.4
423	Merchant Wholesalers, Durable Goods	-80.3
339	Miscellaneous Manufacturing	-72.4
322	Paper Manufacturing	-71.8
562	Waste Management and Remediation Services	-68.8
622	Hospitals	-64.0
332	Fabricated Metal Product Manufacturing	-51.8
312	Beverage and Tobacco Product Manufacturing	-41.4
722	Food Services and Drinking PlacesT	-20.4

**Table OA-2.** Covariate balance: Bank exposure to trade uncertainty and bank characteristics

This table reports OLS estimates from a regression of the baseline bank exposure to trade uncertainty on bank characteristics: size (log-total assets), capital (common equity/total assets), deposits (core deposits/liabilities), and specialization. Regressions use bank characteristics for every year of the regressions sample between 2016 and 2019 and stacked as a panel across 2016–2019. Standard errors are robust. \*\*\* 1%, \*\*5%, and \*10%.

	(1)	(2)	(3)	(4)	(5)
	<b>Bank exposure to trade uncertainty</b>				
Year:	<b>2016</b>	<b>2017</b>	<b>2018</b>	<b>2019</b>	<b>2016–2019</b>
Size (log-assets)	0.050 (0.046)	0.050 (0.047)	0.043 (0.038)	0.053 (0.040)	0.058 (0.041)
Capital (common equity/total assets)	-0.027 (0.033)	-0.030 (0.029)	-0.038 (0.031)	-0.026 (0.035)	-0.004 (0.017)
Core deposits (% of liabilities)	-0.003 (0.003)	-0.001 (0.003)	-0.000 (0.002)	0.001 (0.002)	-0.002 (0.003)
Specialization	0.308 (0.296)	0.308 (0.322)	0.216 (0.246)	0.246 (0.300)	0.392 (0.288)
Observations	30	30	29	28	171
$R^2$	0.219	0.221	0.205	0.152	0.216

**Table OA-3.** Additional lending terms: Collateral Requirements

This table shows OLS estimates for a regression of loan collateral requirements on bank exposure to trade uncertainty. The dependent variable is a dummy variable that takes value one for secured loans and zero otherwise. All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)
	<b>Loan is Secured</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure $\times$ Post	0.064*** (0.016)	0.077*** (0.019)
Observations	924,163	657,467
$R^2$	0.892	0.890
Bank controls	Y	Y
Bank controls $\times$ Post	Y	Y
Firm $\times$ Quarter FE	Y	Y
Firm $\times$ Bank FE	Y	Y

**Table OA-4.** Anticipation effects: Drop loan commitments in 2017

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty changing the sample period to drop all loan commitments in 2017 and move the pre-trade war period back by one year. The new sample period refers to 2015:Q1–2016Q4 (before the Trade War) and 2018:Q1–2019:Q4 (during the Trade War). All specification details and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, \*10%, and # 20%.

Dependent variable	(1)	(2)	(3)	(4)
	<b>Loan growth</b>		<b>Loan spread</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure x Post	-0.071* (0.037)	-0.065# (0.043)	0.332*** (0.096)	0.317** (0.108)
Observations	912,849	647,925	474,606	332,162
R-squared	0.353	0.362	0.850	0.850
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y



**Table OA-5. Placebo Tests**

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty on samples that precede the baseline regression sample by one year (panel A) or two years (panel B). All specification details and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

	(1)	(2)	(3)	(4)
	Loan growth		Loan spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. Placebo: 2015-2016 vs 2017-2018</b>				
Bank exposure $\times$ Post	0.022 (0.031)	0.034 (0.033)	0.078** (0.036)	0.044 (0.037)
Observations	939,016	665,828	491,941	344,075
$R^2$	0.342	0.349	0.850	0.851
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
<b>B. Placebo: 2014-2015 vs 2016-2017</b>				
Bank exposure $\times$ Post	0.044 (0.026)	0.037 (0.030)	-0.111*** (0.035)	-0.129*** (0.031)
Observations	930,363	657,446	489,185	340,833
$R^2$	0.344	0.350	0.844	0.844
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table OA-6.** Bank portfolio rebalancing from C&I lending to other types of assets

This table shows OLS estimates for a regression of bank-level total asset growth, loan-to-asset ratio, securities-to-asset ratio, and cash-to-asset ratio on bank exposure to uncertainty. The data are at the bank-quarter level over the period between 2016:Q1 and 2019:Q4 for the banks in our baseline FR Y-14Q sample. Bank exposure to trade uncertainty is measured as the average of the difference in trade uncertainty across sectors (between 2016:Q1–2017:Q4 and 2018:Q1–2019:Q4), weighted by initial bank loans shares to those sectors (See [Section 2.2](#) for the construction of the variable). The dummy variable *Post* takes value of one for the period 2018:Q1–2019:Q4 and zero for the period 2016:Q1–2017:Q4. Standard errors are double clustered at the quarter and bank level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

	(1) Total asset Growth	(2) Loans % Assets	(3) Securities % Assets	(4) Cash % Assets
<b>A. Baseline</b>				
Bank exposure $\times$ Post	0.071 (0.041)	-0.042*** (0.010)	0.003* (0.001)	0.009 (0.012)
Observations	448	452	452	452
$R^2$	0.352	0.995	0.976	0.971
<b>B. By bank capital: Equity/assets</b>				
Bank exposure $\times$ Post $\times$ Low-capital	0.080* (0.038)	-0.045*** (0.011)	0.003* (0.001)	0.009 (0.012)
Bank exposure $\times$ Post $\times$ High-capital	0.084 (0.160)	-0.048 (0.033)	-0.000 (0.006)	0.057 (0.034)
p-value t-test $H_a :  1  >  2 $	-	-	-	0.00149
Observations	448	452	452	452
$R^2$	0.375	0.995	0.978	0.972
<b>C. By bank capital: CET1 stress test ratio</b>				
Bank exposure $\times$ Post $\times$ Low-capital	0.055 (0.047)	-0.054*** (0.015)	0.003* (0.002)	0.012 (0.014)
Bank exposure $\times$ Post $\times$ High-capital	0.276*** (0.092)	-0.010 (0.013)	0.002 (0.003)	0.012 (0.024)
p-value t-test $H_a :  1  >  2 $	-	-	-	0.1335
Observations	373	374	374	374
$R^2$	0.553	0.996	0.980	0.978
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y

**Table OA-7.** Horse-races with bank exposure to non-trade uncertainty and overall sentiment

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty in a horse-race with (a) bank exposure to non-trade uncertainty and (b) bank exposure to overall sentiment. Bank exposure to non-trade sources of uncertainty is obtained in the same way as bank exposure to trade uncertainty, however instead of the trade uncertainty index we use the first principal component of all sectoral uncertainty indexes other than trade (economic policy and budget, environment, institutions and political processes, health care, security and defense, tax policy, and technology and infrastructure). Bank exposure to changes in overall sentiment is computed in the same way as bank exposure to trade uncertainty. All specification details, sample period, and controls as in Table 2. Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	Loan growth		Loan spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. Control for bank exposure to non-trade uncertainty</b>				
Bank exposure to (trade) uncertainty $\times$ Post	-0.103*** (0.030)	-0.115*** (0.036)	0.261*** (0.084)	0.288*** (0.095)
Bank exposure to non-trade uncertainty $\times$ Post	-0.030 (0.029)	-0.036 (0.032)	0.048 (0.031)	0.077** (0.034)
Observations	925,465	658,123	481,152	337,955
$R^2$	0.342	0.350	0.856	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
<b>B. Control for bank exposure to overall sentiment</b>				
Bank exposure to (trade) uncertainty $\times$ Post	-0.094** (0.036)	-0.085* (0.041)	0.284*** (0.073)	0.317*** (0.078)
Bank exposure to overall sentiment $\times$ Post	-0.013 (0.031)	-0.050 (0.037)	-0.047 (0.063)	-0.066 (0.060)
Observations	925,465	658,123	481,152	337,955
$R^2$	0.342	0.350	0.856	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table OA-8.** Control for exchange rate effects through exporting firms

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty controlling for bank exposure to the tradable-goods producing sectors interacted with the USD broad index. We follow [Desai et al. \(2008\)](#) and classify non-tradable sectors to include construction, retailers, transportation, and recreation. (Utilities and financial firms are excluded from our baseline sample.) All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	<b>Loan growth</b>		<b>Loan spread</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure $\times$ Post	-0.098*** (0.031)	-0.107** (0.037)	0.322*** (0.084)	0.342*** (0.090)
Bank exposure to tradable-goods sectors $\times$ USD broad index	-0.001 (0.008)	0.002 (0.011)	0.105* (0.049)	0.112** (0.050)
Observations	872,735	620,126	450,864	315,130
$R^2$	0.343	0.352	0.846	0.846
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table OA-9.** Effects by loan type: Credit lines vs. Term loans

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty opening up the main difference-in-differences coefficient by loan type: credit lines vs. term loans. All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	<b>Loan growth</b>		<b>Loan spread</b>	
	<b>All firms</b>	<b>Low-uncertainty firms</b>	<b>All firms</b>	<b>Low-uncertainty firms</b>
Bank exposure $\times$ Post $\times$ Credit line	-0.061** (0.025)	-0.049* (0.028)	0.255*** (0.081)	0.271** (0.093)
Bank exposure $\times$ Post $\times$ Term loan	0.018 (0.036)	-0.033 (0.043)	0.235** (0.086)	0.272** (0.103)
Observations	817,911	580,321	448,606	313,629
$R^2$	0.380	0.384	0.890	0.892
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table OA-10.** Control for bank cyclicalilty and oil price fluctuations

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty controlling for bank cyclicalilty in level and interaction with *Post* (panel A) and dropping oil firms from the baseline sample (panel B). Bank cyclicalilty is a time-invariant bank-level variable representing the correlation between the bank's C&I loan growth and the growth rate of banking sector assets (the correlation is obtained by regressing each bank's C&I loan growth on banking sector asset growth for each bank in the dataset, over the period 1985:Q1–2021:Q2, using quarterly Call Report data and assigning each BHC in the Y-14Q dataset to the main commercial bank in that BHC from the Call Report). Oil firms are defined as those in the 2-digit NAICS sector “Mining, quarrying, and oil and gas extraction.” All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	Loan growth		Loan spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. Control for bank cyclicalilty</b>				
Bank exposure $\times$ Post	-0.053* (0.026)	-0.071** (0.032)	0.252*** (0.066)	0.284*** (0.077)
Bank cyclicalilty $\times$ Post	0.029*** (0.006)	0.023*** (0.005)	-0.009 (0.029)	0.001 (0.029)
Observations	925,465	658,123	481,126	337,942
$R^2$	0.342	0.350	0.856	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
<b>B. Drop oil firms</b>				
Bank exposure $\times$ Post	-0.106*** (0.030)	-0.117*** (0.036)	0.236** (0.086)	0.255** (0.101)
Observations	876,802	609,751	451,075	308,043
$R^2$	0.337	0.343	0.856	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y

**Table OA-11.** Additional results: Credit line utilization

This table shows OLS estimates for a regression of credit line utilization rates on a dummy variable for high-uncertainty firms in interaction with *Post*. The estimates are shown for firm-level data where the credit line utilization rates are averaged, for each firm, across its lender banks. High-uncertainty firm is a dummy variable taking value one for firms in sectors above the 75<sup>th</sup> percentile of distribution of changes in average trade uncertainty between 2016–2017 and 2018–2019, and zero otherwise. Column 2 includes the following firm controls in level and interacted with *Post*: size (log-assets), liquidity (cash and marketable securities/assets), tangibility (tangible assets as a share of total assets), interest coverage ratio (EBITDA/total interest expense), ROA (return on assets) and real sales growth. Standard errors are clustered at the firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable:	(1)	(2)
	<b>Credit line utilization rate</b>	
High-uncertainty firm $\times$ Post	0.0048** (0.0020)	0.0043** (0.0020)
Observations	618,160	578,028
$R^2$	0.795	0.798
Firm controls		Y
Firm controls $\times$ Post		Y
Firm FE	Y	Y
State $\times$ Quarter FE	Y	Y

**Table OA-12.** Alternative measures of “spillover” firms and baseline specifications with no FE

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty to low-uncertainty “spillover firms” using alternative definitions of these firms (panel A) and using no fixed effects (panel B). In columns 1–2 “spillover firms” are those firms in sectors that did not receive tariffs. In columns 3–4, they are the low-uncertainty firms from the baseline analysis and we further drop few remaining trade finance loans. All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1) Loan growth	(2) Loan spread	(3) Loan growth	(4) Loan spread
	Firms in no-tariff sectors		Low-uncertainty firms Drop trade finance loans	
A. Alternative measures of spillover firms				
Bank exposure $\times$ Post	-0.070* (0.033)	0.238*** (0.078)	-0.091** (0.036)	0.278*** (0.091)
Observations	636,703	333,020	649,429	333,894
$R^2$	0.344	0.857	0.350	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
B. Baseline with no fixed effects				
Bank exposure $\times$ Post	-0.042*** (0.014)	0.500*** (0.037)	-0.066*** (0.017)	0.596*** (0.047)
Bank exposure	0.112*** (0.010)	-0.308*** (0.037)	0.136*** (0.012)	-0.694*** (0.048)
Post	-0.258*** (0.081)	-0.910*** (0.186)		
Observations	1,536,325	863,149	1,075,899	596,900
$R^2$	0.003	0.010	0.005	0.014
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Quarter FE			Y	Y



**Table OA-13.** Robustness to granular loan-type fixed effects

This table shows OLS estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty controlling for loantype $\times$ quarter fixed effects (panel A) and firm $\times$ loantype $\times$ quarter fixed effects (panel B). Loantype is given by (i) trade finance loans, (ii) loans secured by fixed assets and real estate, cash and marketable securities, or blanket liens (roughly capturing asset-based loans) and (iii) loans secured by accounts receivable and inventory (earnings-based loans). All specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	Loan growth		Loan spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. With Loan Type <math>\times</math> Quarter FE</b>				
Bank exposure $\times$ Post	-0.084** (0.035)	-0.098** (0.042)	0.263*** (0.078)	0.287*** (0.087)
Observations	925,465	658,123	481,152	337,955
$R^2$	0.359	0.363	0.858	0.858
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
Loan-type $\times$ Quarter FE	Y	Y	Y	Y
<b>B. With Firm <math>\times</math> Loan Type <math>\times</math> Quarter FE</b>				
Bank exposure $\times$ Post	-0.092** (0.033)	-0.097** (0.038)	0.245*** (0.082)	0.272** (0.094)
Observations	924,523	657,440	480,489	337,486
$R^2$	0.362	0.369	0.858	0.858
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
Firm $\times$ Loan-type $\times$ Quarter FE	Y	Y	Y	Y

**Table OA-14.** Baseline regression estimates with WLS and alternative trade uncertainty measure

This table shows Weighted Least Squares (WLS) estimates for a regression of loan growth and spreads on bank exposure to trade uncertainty (panel A) and estimates for the same regression using a measure of bank exposure to trade policy uncertainty from [Caldara et al. \(2020\)](#) (panel B). In panel A, analytical weights are 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 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, bank exposure to trade policy uncertainty is computed in the same way as the baseline measure of bank exposure to trade uncertainty, but using instead the uncertainty data from [Caldara et al. \(2020\)](#). All other specification details, sample period, and controls as in [Table 2](#). Standard errors are double clustered at the quarter and bank-firm level. Significance: \*\*\* 1%, \*\*5%, and \*10%.

Dependent variable	(1)	(2)	(3)	(4)
	Loan Growth		Loan Spread	
	All firms	Low-uncertainty firms	All firms	Low-uncertainty firms
<b>A. Weighted Least Squares</b>				
Bank exposure $\times$ Post	-0.128*** (0.034)	-0.130*** (0.039)	0.308** (0.114)	0.331** (0.128)
Observations	925,465	658,123	481,152	337,955
$R^2$	0.350	0.357	0.861	0.861
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y
<b>B. Robustnes to <a href="#">Caldara et al. (2020)</a> measure</b>				
Bank exposure to (trade policy) uncertainty $\times$ Post	-0.011 (0.014)	-0.016 (0.016)	0.133*** (0.039)	0.127*** (0.042)
Observations	925,465	658,123	481,152	337,955
$R^2$	0.342	0.350	0.856	0.856
Bank controls	Y	Y	Y	Y
Bank controls $\times$ Post	Y	Y	Y	Y
Firm $\times$ Quarter FE	Y	Y	Y	Y
Firm $\times$ Bank FE	Y	Y	Y	Y