Bank Financing of Global Supply Chains*

Laura Alfaro
Harvard Business School,
NBER, CEPR

Mariya Brussevich
International Monetary Fund
Ibmec-RJ

Camelia Minoiu
Federal Reserve Bank
of Atlanta

Andrea Presbitero
International Monetary Fund
CEPR

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Finding new suppliers is costly, so most importers source inputs from a single country. We examine the role of banks in mitigating trade search costs during the 2018–2019 U.S.-China trade tensions. We match data on shipments to U.S. ports with the U.S. credit register to analyze trade and bank credit relationships at the bank-firm level. We show that importers of tariff-hit products from China were more likely to exit relationships with Chinese suppliers and to find new suppliers in other Asian countries. To finance their geographic diversification, tariff-hit firms increased credit demand, drawing on bank credit lines and taking out loans at higher rates. Banks offering specialized trade finance services to Asian markets eased both financial and information frictions. Tariff-hit firms with specialized banks borrowed at lower rates and were 15 pps more likely and 3 months faster to establish new supplier relationships than firms with other banks. We estimate the cost of searching for suppliers at $1.9 million (or 5% of annual sales revenue) for the average U.S. importer.

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*Authors' e-mail addresses: Laura Alfaro (lalfaro@hbs.edu), Mariya Brussevich (brussevich@gmail.com), Camelia Minoiu (Camelia.Minoiu@atl.frb.org), and Andrea Presbitero (apresbitero@imf.org). We are grateful to Viral Acharya, JaeBin Ahn, Salome Baslandze, Catherine Casanova, Ricardo Correa, Rebecca De Simone, Julian di Giovanni, Simon Fuchs, Ruben Gaetani, Pierre-Olivier Gourinchas, Peter Haslag, Gazi Kabas, Fernando Leibovici, Rodrigo Leite, Isabelle Mejean, Tomasz Michalski, Emanuel Moench, Lars Norden, Evren Ors, Tarun Ramodarai, Kim Ruhl, Felipe Saffie, Peter Schott, Toshitaka Sekine, Larry Wall, Jon Willis, and participants at numerous conferences and seminars for helpful comments and discussions. We thank Yuritzy Ramos for outstanding research assistance. This project is supported by the Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro, Grant/Award Number: SEI-260003/000532/2023. The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Atlanta, the Federal Reserve System, or the IMF.

1 Introduction

In recent years, rising trade tensions, geopolitical risks, and the pandemic have disrupted global supply chains and trade patterns. In response, U.S. importers have started a "great reallocation" that is changing the geography of international trade (Fajgelbaum *et al.*, 2024). Finding new trade partners involves significant costs (Grossman *et al.*, 2024), so relationships along the supply chain are sticky and even larger importers rely on suppliers from a single country (Antras *et al.*, 2017). Yet, little is known about how firms overcome search frictions to reconfigure supply chains, particularly in the presence of financial frictions.[1] This paper asks whether and how commercial banks help importers mitigate search frictions and support supply chain resilience to shocks.

We match, for the first time, two administrative datasets on trade and bank relationships to document the critical role of banks in supporting U.S. importers reconfigure supply chains during the rise of U.S.-China trade tensions. Tariff-hit firms—which were importing products from China subject to the 2018–2019 tariffs—are more likely to exit relationships with Chinese suppliers and find new suppliers in other Asian countries after the tariffs. Consistent with tariffs as a salient input cost shock, tariff-hit importers increase their demand for bank credit, drawing more heavily on credit lines and obtaining new credit at higher rates. We estimate the dollar value of the search cost over the average period it takes to establish a new Asian supplier relationship at $1.9 million (or 5% of annual sales revenue).

An important novelty of our paper is to show that U.S. importers differ in the ability to find new suppliers depending on the business model of their bank. Tariff-hit firms that borrow from banks with expertise in trade finance services to Asian markets (to which we refer as "specialized banks") obtain cheaper credit than other firms. Our evidence suggests that specialized banks not only provide cheaper loans, but also leverage their expertise of foreign markets to help borrowers with information about supplier networks. As a result, tariff-

[1] In fact, many studies examine firms' supply chain decisions in isolation of financial constraints; see, e.g., Alessandria *et al.* 2021 and Fajgelbaum and Khandelwal (2022) for reviews of the recent research.

hit importers with specialized banks are 15 percentage points (pps) more likely to find new suppliers outside China and a little more than 3 months faster to establish a new relationship; they also grow their Asian import shares by 5.6 pps more than tariff-hit importers with other banks. Overall, our results emphasize the value of relationships with specialized banks in supporting supply chain realignment through both credit and information channels.

To shed light on the role of banks in the reallocation of global supply chains, we exploit the input cost shock induced by the introduction of wide-ranging trade tariffs in 2018–2019 by the U.S. on (mostly intermediate inputs and capital goods) imports from China, coupled with heterogeneous firm exposure to the shock. We center the analysis on China because it was the top supplier of goods to the U.S. and most tariffs targeted products imported from China, whereas those affecting other trade partners were product-specific.

A key contribution of our analysis is to merge large datasets on trade (at the firm-to-firm level), bank relationships (at the bank-firm level), and tariffs (at the product level) for U.S. non-financial firms. These datasets contain detailed information on international trade relationships (imports, exports, and identity of trade partners) coupled with confidential bank-to-firm credit relationship that are matched to firm and bank balance sheets. These data afford us several advantages compared to publicly available data. First, we are able to document supply chain reallocation at the product, importer, and supplier level as opposed to aggregate country and product level. Second, we can identify the role of bank financing for supply chain realignment at the firm-bank level as opposed to relying on industry-level proxies of financial constraints. Third, these data allow us to document new facts about the industry distribution and balance sheets of bank-dependent U.S. importers, which have so far eschewed analysis due to the scarcity of private firm data. Private firms (with an average bank debt share of 42%) account for the vast majority of firms in our dataset.[2]

In detail, we use shipment-level data from S&P Panjiva Supply Chain Intelligence (Pan-

[2] Out of approximately 26,000 U.S. importers in the credit register, 95% are private firms. The average bank-to-total debt ratio of 42% for these firms likely underestimates the true extent of bank dependence because it is based solely on debt from banks included in the credit register.

jiva in short) on U.S. firms' import volumes and suppliers. Panjiva covers the universe of maritime trade shipments (accounting for the bulk of international trade) to the U.S. since 2007.[3] These data have unique firm identifiers that enable us to track relationships between U.S. importers and their foreign suppliers across products and countries. To identify the U.S. importer-supplier relationships affected by the 2018–2019 tariffs, we combine these data with information on tariffs imposed by the U.S. on Chinese imports. Then, we merge in supervisory loan-level data from the Federal Reserve Y-14Q H1 Corporate Loan Data Schedule (Y14 in short), which contains quarterly information about bank loan contracts since 2012. Matching the Panjiva and Y14 datasets allows us to present the first firm-level evidence on importers' use of bank financing in the reallocation of supply chains (Section 2).

Our empirical analysis is guided by a framework that considers the fixed cost of establishing a new supplier relationship in a given market and banks specialized in that market that can offer better lending terms.[4] In this framework, supply chain realignment increases with tariffs and specialized lenders can lower the cost of matching to new suppliers. To establish the firm-level effects of tariffs on trade reallocation and the role of specialized banks in mitigating search costs, we proceed as follows.

First, we document that during the escalation of trade tensions, tariff-hit importers pared back trade activities with China and increased them with other Asian countries (Section 3). Figure 1 depicts the trade reallocation for U.S. firms since 2018, notably a reduction in import shares from China and commensurate increase in import shares from Asia (excluding China) and the rest of the world. The figure also shows that changes in import shares become notable a few quarters after the first wave of tariffs in early 2018. Difference-in-differences (DiD) regressions on firm-product-level data show that tariff-hit importers are more likely to terminate relationships with Chinese suppliers and enter new relationships with Asian suppliers outside China. As a result, the import share from China declines by 86%, whereas the import share from Asian markets (excluding China) increases by 47% during 2018–2019.

[3] In recent years, ships deliver more than 80% of total international trade by value (UNCTAD, 2021).

[4] See Appendix A-I.

Second, we document that the time it takes to find a new supplier varies by firm and product types, suggesting that search frictions induce costly matching to new suppliers (Section 4). Indeed, Cox proportional hazards regressions show that diversified U.S. importers who had suppliers in Asia before trade tensions—and hence prior knowledge of the region—were faster in finding new suppliers outside China. In addition, firms importing products characterized by a high degree of specificity and thus facing higher search costs (Martin *et al.*, 2024) took longer to find new suppliers. The direct cost of tariffs and the additional search costs associated with setting up new supplier relationships motivate us next to examine the role of specialized banks in facilitating this reallocation.

Third, we analyze bank credit flows to tariff-hit U.S. importers (Section 5) and show that tariff-hit importers increased their demand for bank credit, as predicted by trade models with search costs (Grossman *et al.*, 2024). Loan-level DiD regressions show that tariff-hit firms increase their credit line utilization rates during the escalation of trade tensions compared to other firms. Corporate credit lines are committed lines of credit that can be tapped with no restrictions when covenants are not breached (Sufi, 2009), therefore higher credit line utilizations indicate higher credit demand. In addition, tariff-hit firms obtain new loans at higher interest rates (by close to 18 bps), which is also suggestive of increased credit demand.

Fourth, we turn to the role of banks in helping firms mitigate search frictions in trade (Section 6). Some banks should be better positioned for this purpose due to specialization in certain services (such as trade finance) and foreign markets (such as Asia). Support from specialized lenders can materialize through different channels. Specialized banks have superior knowledge of markets or industries where firms operate, which translates into better loan terms (a *credit* channel). We show that tariff-hit importers with specialized banks obtain new loans at interest rates lower by close to 19 bps than those with other banks. Specialized bank can also offer information about potential suppliers in foreign markets through advisory and consulting services (an *information* channel). Our analysis reveals that differences in the cost of credit for importers with specialized banks translate into a higher likelihood and faster speed of finding new suppliers outside China. To make sure that the results reflect the value of relationships with banks specialized in trade finance to Asian markets and not those of global banks more generally, we show that relationships with banks specialized in Europe (and not Asia) have no effect on credit or trade outcomes.

Lastly, we provide three pieces of evidence supporting an "information channel" by which specialized banks use their expertise of foreign markets to help their clients find suppliers. First, we show that firms with specialized banks are more likely to match to new Asian suppliers which were either clients of other U.S. banks or suppliers to other U.S. firms before the tariffs. Second, we restrict our analysis to importers which are less financially constrained (measured based on balance sheet size or credit rating) and thus less likely to need credit. Restricting the analysis to these less constrained firms, we show that those firms with specialized banks are better able to establish new supplier relationships even though they do not obtain better loan terms than less constrained firms with other banks. Third, we examine the income statements of foreign subsidiaries of U.S. banks and document that Asian subsidiaries of specialized banks experience higher advisory fee income growth than non-Asian subsidiaries during 2018–2019.

In additional results, we find no evidence of substitution between trade credit from Chinese suppliers and bank credit. Furthermore, specialized banks' role in enabling firms to diversify geographically during the tariff period is not accompanied by increased risk-taking: neither non-performing loans nor charge-offs increase differentially at specialized banks. Several robustness checks further validate our results. We show, for instance, that the baseline results are invariant to (a) using a nearest-neighbor matching estimator; (b) placebo tests that move the period of analysis back by two or three years or change the geographic component of the bank specialization definition to European markets instead of Asian markets; (c) controlling for relationship banking; and (d) allowing for staggered tariff treatment of U.S. importers capturing the enactment of tariffs in several waves.

Contribution to the literature. This paper is related to several strands of literature. First, our paper adds to the literature on the role of commercial banks in facilitating international trade (Manova, 2012; Michalski and Ors, 2012; Antras and Foley, 2015; Bronzini and D'Ignazio, 2017; Claessens and Van Horen, 2021; Berthou *et al.*, 2024; Kabir *et al.*, 2024) and firms' participation in global supply chains (Ersahin *et al.*, 2024a; Minetti *et al.*, 2019; Foley and Manova, 2015). Many studies show that banks exacerbate sectoral shocks to trade-oriented firms (see, e.g., Chaney, 2016; Chor and Manova, 2012; Klein *et al.*, 2002), including by reallocating credit when they receive balance sheet shocks (Amiti and Weinstein, 2011; Federico *et al.*, 2023). However, the literature has paid less attention to commercial banks as potential absorbers of real sector shocks.[5] Benguria and Saffie (2024) show that industry-level financial constraints hinder the reallocation of U.S. exports away from retaliating countries. Our paper brings complementary evidence on the effect of bank financing on firms' trade activities, but focuses on bank credit to U.S. importers, most of which are private and bank-dependent firms. In addition, we emphasize the value of importers' relationships with specialized banks in overcoming search frictions in trade.

Second, our paper relates to the literature on the salience of specialized banks. Banks that specialize in lending to firms in particular markets or industries are more likely to experience increased loan demand when their borrowers suffer negative shocks, but also have the incentive to maintain loan supply to reduce the likelihood of defaults and balance sheet losses (Brancati, 2022; Blickle *et al.*, 2023; Berthou *et al.*, 2024). Paravisini *et al.* (2023) show that banks with outsized lending exposure to export markets face higher credit demand from exporting firms seeking to enter new export markets. Our results echo these findings in that U.S. firms seeking to reconfigure supply chains demand more credit from their specialized banks. However, our paper focuses on a distinct importer channel and emphasizes that banks with expertise in foreign markets help their borrowers not only with credit, but also with information services. In addition, our analysis suggests that firm relationships with

[5] Berger *et al.* (2023) show that local presence of global bank subsidiaries is associated with weaker transmission of pandemic-related trade disruptions in Brazil.

specialized banks are valuable not only in settings where informational asymmetries are large—as is the case for smaller and opaque firms—but also for larger established importers.

Third, our paper speaks to the international trade literature, which argues that relational contracting is critical for supply chain formation and that supply chain disruptions can generate search frictions (Alfaro *et al.*, 2019; Monarch, 2022; Grossman *et al.*, 2024; Fontaine *et al.*, 2023; Monarch and Schmidt-Eisenlohr, 2023).[6] Trade models treat fixed costs associated with firm matching to suppliers or buyers as sunk costs and predict "lock-in" effects in buyer-supplier relationships. Whereas theoretical predictions of buyer-supplier relationship stickiness are generally supported empirically, the literature is largely silent on the financing mechanisms used by firms to form new supplier relationships. Our paper adds to this literature by presenting new evidence on the role of commercial banks in facilitating firms' realignment of supply chains across foreign markets, not only through the provision of credit but also by reducing barriers to information diffusion about potential suppliers (Allen, 2014).

Finally, we contribute to the literature on the domestic and international impacts of the 2018–2019 trade tensions. Existing studies show the tariffs had an adverse effect on U.S. real activity and consumer prices (see Fajgelbaum and Khandelwal, 2022; Caliendo and Parro, 2023, for a review). Alfaro and Chor (2023), Freund *et al.* (2024), Goldberg and Reed (2023) and Gopinath *et al.* (2025) document a significant reallocation of U.S. imports from China to other countries. In addition, tariffs-driven exits from supplier relationships were associated with lower export activity for U.S. firms (Handley *et al.*, 2024). We expand this literature in two ways. First, we document the reconfiguration of input sourcing by U.S. firms away from China and toward other markets at the firm level, on both the intensive and extensive margins of imports. Second, we highlight a bank financing channel that mitigates financial frictions in importers' reconfiguration of supply chains.

[6] More broadly, supply chain disruptions are associated with large macroeconomics costs (see, e.g., Acemoglu and Tahbaz-Salehi (2024); Alessandria *et al.* (2023); Di Giovanni *et al.* (2023); Bai *et al.* (2024)) and idiosyncratic shocks to firms can generate aggregate fluctuations (Di Giovanni *et al.*, 2014, 2018; Kramarz *et al.*, 2020; Di Giovanni *et al.*, 2024).

2 Data, Importer Characteristics, and Diversification

In this section we describe our main data sources and the characteristics of importers in the Panjiva-Y14 matched sample. We also present novel estimates of the degree of supplier diversification of U.S. importers across countries.

2.1 Data Sources

In 2018–2019, the U.S. imposed tariffs on more than 13,000 10-digit HS product codes and over 100 trade partners, followed by retaliatory tariffs from some of these partners on specific U.S. exports. China was at the forefront of these tensions, with U.S. imports from China valued at more than $350 billion subject to tariff rates between 10% and 25%.[7] To study the effects of the 2018–2019 tariffs on U.S. firms' supply chains and access to credit, we assemble a novel dataset on firm-level trade relationships and firm-bank lending relationships spanning the 2013–2022 period. Most baseline analysis is conducted on the 2016–2019 sample period to avoid contaminating factors related to the Covid-19 pandemic. In short, the trade data cover the universe of shipments to U.S. ports and allow us to track firm-to-firm trade relationships. The bank credit data cover a significant share of credit commitments in the U.S. banking sector and provide detailed information for loan contracts to mostly private bank-dependent firms. Below, we discuss each dataset in detail and the process for merging the data for the analysis.

Firm-supplier International Shipment Data. We use shipment-level data from S&P Panjiva Supply Chain Intelligence on U.S. firms' import volumes and suppliers. Panjiva collects bill of lading data from the U.S. Customs and Border Protection (CBP), with information on all maritime imports of U.S. firms, including name and address of the U.S. importer (consignee), an identifier for the foreign supplier, date of import, country of origin, product description and 6-digit HS code, and import volumes in TEU (twenty-foot equivalent

[7] See Bown (2021) for a description of tariff timing and targeted countries.

unit).[8]

A leading advantage of Panjiva is the availability of firm identifiers, which allow us to track bilateral relationships between U.S. importing firms and their foreign suppliers across products and countries and to examine the reorganization of supply chains in response to tariffs *at the firm level*. Another advantage is the availability of the U.S. firm's name and address, which enables us to match the firms in Panjiva with the bank credit data (described below). We are also able to identify shipments from U.S. firms' affiliates abroad using S&P data on foreign firms' ownership. A small share of firms with at least one shipment from a foreign affiliate during 2016–2019 (to which we loosely refer as "multinationals") are excluded from the regression analysis. Thus, we only examine shipments from non-affiliated suppliers.

Given that Panjiva contains information on maritime shipments only, it is best suited for studying supply chain reallocation towards countries with which the U.S. trades by sea. For this reason, our analysis centers on supply chain relationships between U.S. importers and Asian suppliers. As we cannot assess the extent of supply chain reallocation towards Mexico and Canada, for which most trade occurs through airborne and land shipments, we also exclude all products that U.S. firms predominantly import from Mexico and Canada.[9]

Despite its sole focus on maritime shipments, aggregated Panjiva data track the U.S. Census data closely during our sample period (see Figure A1 versus Figure 1 for a comparison of import shares from China, Asia excluding China, and rest of the world over 2013–2019).

[8] S&P Panjiva Supply Chain Intelligence makes the bill of lading data available for imports and exports of 17 countries. We focus on the U.S. import sample, in which we are able to track the names and identifiers of foreign suppliers to U.S. importers. Flaaen *et al.* (2023) provide a detailed overview of the Panjiva data, highlighting its advantages and limitations, including the fact that some firm names are redacted and their shipments cannot be used in our analysis. For a detailed discussion of this issue, see Appendix A-II.

[9] We investigate the extent of export re-routing by Chinese firms via foreign affiliates, which could contribute "hidden exposure" of U.S. firms to Chinese suppliers (Baldwin *et al.*, 2023). Using information on suppliers' foreign parents from S&P Capital IQ, we find that in the case of Mexico and Vietnam, for example, less than 1% of suppliers belong to a Chinese parent firm. For Vietnam, this number increased from 0.4% in 2016 to 0.7% in 2023, while for Mexico, it remained stable between 0.3% and 0.5% during this period. The role of potential re-exporting (re-routing) via Chinese-owned multinationals' offshore subsidiaries is thus limited in our aggregate estimates.

Bank-firm Loan-level Data. To examine bank credit outcomes, we use loan-level data from the FR Y-14Q H1 Corporate Loan Data Schedule. This supervisory dataset is part of the Dodd-Frank Act Y-14Q data collection effort and contains quarterly information on commercial and industrial (C&I) loans that are larger than $1 million. The data are collected from the 43 largest bank holding companies (BHCs) subject to stress tests (with more than $100 billion in total consolidated assets). These data cover between two-thirds and three-quarters of total U.S. C&I loans to U.S. non-financial firms (Chodorow-Reich *et al.*, 2022; Favara *et al.*, 2021). Y14 offers detailed information about bank-firm loan contracts. For each loan, we know if it is a corporate credit line and can compute the credit line utilization rate (defined as the ratio between the total utilized amount and the total commitment). Furthermore, we observe contractual features such as the interest rate (set to zero for credit lines that are fully undrawn and thus dropped from the analysis), maturity, probabilities of default, and loan performance (non-performing and charged-off loan flags).

For each borrower, the lenders report several balance sheet and income statement variables, including total assets, total debt, cash holdings, and profitability (return on assets). These data are reported on a yearly basis for most firms and on a quarterly basis for a minority of (mostly listed) firms. In the analysis, all firm variables are measured at end-2017 (when available, or end-2016 otherwise) and are thus predetermined relative to the tariffs.

Panjiva and Y14 Matching. To study the bank credit outcomes of U.S. importers, we need to match firm records in the Panjiva and Y14 datasets. The two datasets do not contain common identifiers. Therefore, we start by cleaning the names of the firms in a bank relationship or with a shipment record. Then, we employ an exact and fuzzy name-matching procedure, which produces highly accurate name matches for about 68,000 importers corresponding to 56,000 bank borrowers. We also exploit information on U.S. firms' ultimate corporate parent names from S&P Capital IQ, which further allows the matching of some importers to their parent firms in the Y14 data. Our matching procedure is conservative in that we check and discard, by hand, any fuzzy matches that appear false, even if those firms have high name similarity. We also check the final list of matches for accuracy. In the matched sample, we have balance sheet information for approximately 12,500 firms at the end of 2017.[10]

Tariff Data. We use data on tariffs imposed by the U.S. on its trading partners in 2018 and 2019 from Fajgelbaum *et al.* (2020) and Fajgelbaum *et al.* (2024). These data identify 10-digit HS products and countries targeted by the 2018–2019 tariffs and document the month of the tariff change and the applied rate. In our Panjiva-Y14 matched firm-product level sample, 3,156 HS 6-digit level products out of a total of 4,757 products imported by U.S. firms in 2016–2017 were affected by tariffs. Furthermore, 86% of products (or 3,090 HS 6-digit level products) imported from Chinese suppliers received tariffs in 2018–2019. Tariff hikes on 78% of products went into effect in 2018, and the rest of the tariff hikes were implemented by 2019:Q3.

2.2 Importer Characteristics and Supplier Diversification

Who Are the Importers? The Panjiva-Y14 matched dataset allows us to document new facts about U.S. importers in a credit relationship with Y14-reporting banks. During the sample period 2016–2019, 29% of firms are importers and one in ten firms have both importing and exporting activities. Importers (especially those with Chinese suppliers) are concentrated in manufacturing and wholesale trade industries and account for a significant share of economic activity in Y14. The prevalence of importers and exporters in the Y14 data reflects the fact that bank portfolios are titled towards industries with high shares of tangible assets that can be pledged as loan security, such as manufacturing. In addition, importers are more likely to be multinationals (in the sense of having affiliated suppliers

[10] Appendix A-II describes the matching procedure in detail. Despite our effort to conduct an accurate matching procedure across the Panjiva and Y14 datasets, there may still be measurement errors in the matching of firms. False or missed matches in the treatment and control groups would lead, if random, to attenuation bias on the estimated coefficients.

abroad) and publicly listed. They are also larger, have less cash, and lower leverage than other firms. Appendix A-III provides a more detailed description of these firms.

How Diversified Are the Importers? Our estimates suggest that the median importer is remarkably undiversified across countries and thus faces significant country risk. We calculate the number of source countries per product in 2016 and 2022 and benchmark our estimates against Antras *et al.* (2017). Specifically, we compute the mean, median, and maximum number of (HS 6-digit) product-specific source countries in firm-product-country level data; then, we report the mean, median, and 95th percentile statistics in the cross-sectional distribution of firms. As seen in Panel A of Table 2, the median U.S. firm sourced products from a single country in both years. At the 95th percentile, firms imported from an average of about 3 countries in 2016 and 2 countries in 2022. Estimates in Antras *et al.* (2017) show a more diversified base of source countries in 2007 (at the HS 10-digit product level). At face value, these estimates together suggest diversification has in fact declined in the past two decades. In Panel B of Table 2 we turn to the number of individual suppliers within-product and within-country. These statistics, too, show a decline in diversification, with the average firm importing a given product from a given country from a maximum of 3.05 suppliers in 2016 and 2.62 suppliers in 2022. In addition, the median firm continues to have one supplier (per country per HS 6-digit product).

Tariff-hit Importers vs. Other Firms. In most of the empirical analysis we adopt a DiD approach which allows us to study the realignment of supply chains away from China and the role of bank credit in shaping this realignment by comparing U.S. importers exposed to tariffs with other firms pre/post tariffs. We classify a firm-product pair as "treated" (tariff-hit) if the firm was importing at least one product from China before the rise of trade tensions (2016–2017) that was subject to tariffs during 2018–2019. This approach aggregates to a firm-level treatment such that a firm is treated if at least one of its products is. This definition implies that treatment subsumes most firms with Chinese suppliers before 2018, as 98.5% of such firms were also affected by tariffs, highlighting the wide-ranging nature of the China tariffs.[11] A key concern is that potential differences across the two groups of firms could drive access to credit and capacity to diversify. However, as seen in the Table A3, tariff-hit importers are similar to other firms along key observable characteristics (total assets, leverage, liquidity, and profitability) and lending outcomes (credit line utilization and cost of credit) before the tariffs.

3 Supply Chain Realignment

We analyze changes in U.S. firms' supply chain participation in response to the 2018–2019 tariffs on both the extensive and intensive margins of trade within a narrow product category. We estimate the following baseline trade regression at the firm-product-year level for each market of interest (China and Asia ex-China):

$$\text{Trade Outcome}_{ipt} = \exp[\beta_1 \text{Tariff-hit}_{ip} \times \text{Post}_t + \beta_2 X_i \times \text{Post}_t + \sigma_{ip} + \theta_{pt} + \phi_{kt} + \mu_{st}] + \epsilon_{ipt}, \quad (1)$$

where Trade Outcome$_{ipt}$ is a measure of supply chain participation for firm i importing product p in year t. The trade outcomes are firm-level measures of supply chain participation: (a) dummies for exit from Chinese supplier relationships and entry into relationships with Asian (ex-China) suppliers, (b) the number of Chinese suppliers lost and that of Asian suppliers gained, and (c) import shares based on volumes.[12] Within-product changes in the number of suppliers are calculated as differences between two consecutive years.[13] The tariff-

[11] The academic literature sees the 2018–2019 tariffs as largely unanticipated (Grossman *et al.*, 2024; Alessandria *et al.*, 2024), however, their enactment followed a protracted period of trade negotiations and uncertainty. Anticipation effects in our DiD framework would lead firms to start existing from and entering supplier relationships before the imposition of tariffs and hence work against us finding any significant effects.

[12] As import volume is available at the shipment level and not by product and most shipments (96%) only have one product, we compute import volume shares for single-product shipments only. Table 1 (Panel A) reports descriptive statistics on supplier counts and import shares at the firm-product level. Within firm-product (6-digit HS code level), the average U.S. importer has 1.7 suppliers from China and 2.2 suppliers from Asian countries (ex-China), consistent with figures reported by Monarch (2022).

[13] When a U.S. importer is active in two non-consecutive years, we assign zeros to this importer's supplier counts in the intermediate years. However, we do not assign zeros beyond the first and last year when an

hit dummy variable identifies "treated" firm-product pairs and the control group comprises all importers not subject to tariffs. The Post dummy takes value one during 2018–2019 and zero during 2016–2017. X_i refers to firm-level covariates measured at the end of 2017, including: firm size (log-total assets), leverage (debt-to-asset ratio), liquidity (cash and marketable securities-to-asset ratio), profitability (ROA), and a dummy variable taking value one for firms with at least one export product subject to retaliatory tariffs during the period of analysis. These covariates enter in interaction with the Post dummy.

We include a range of granular fixed effects to soak up unobserved time-varying heterogeneity at the firm, product, state, and industry level, including firm×product (σ_{ip}), product×year (θ_{pt}), state×year (μ_{st}), and industry×year (ϕ_{kt}) fixed effects. In all regression analysis, products are identified at the 6-digit HS code level and industry categories refer to the 3-digit NAICS classification. Furthermore, we drop multinational firms (that is, firms that receive at least one shipment from their own affiliates during the sample period). We estimate Equation (1) using Poisson Pseudo Maximum Likelihood (PPML), which is suitable for count models with a large share of zero values in the dependent variable (Silva and Tenreyro, 2006). Standard errors are double clustered at the firm and product level.

Results. Table 3 reports the estimation results. We find large and statistically significant (at the 1% level) reallocation effects away from China and toward other Asian countries for tariff-hit firms. Coefficient magnitudes are economically sizeable. The probability of exit from a relationship with a Chinese supplier increases by 82% and the probability of entry into a relationship with a new Asian supplier (outside China) increases by 90% for tariff-hit firms after tariffs are imposed (columns 1 and 4). The number of suppliers lost in China increases by 79% and that of suppliers gained outside China increases by 75% (columns 2 and 5). Semi-elasticities below 100% suggest that the shift to new Asian suppliers after dropping a Chinese supplier was not complete during 2018–2019. As U.S. importers respond to the 2018–2019 tariffs by churning suppliers across markets, the import share from China

importer is observed as active.

declines by 86% (column 3) and the import share from other Asian countries increases by 48% for tariff-hit firms (column 6).

Robustness. These findings are robust to the following checks: (a) using the Abadie and Imbens (2011) nearest-neighbor matching estimator (Table A11), (b) adding a firm-specific correction for potential pretrends as in Autor *et al.* (2024) (Table A12), (c) exploiting the staggered timing of tariffs (Table A16), (d) dropping publicly-listed firms (Table A17) or importers from the wholesale and retail sectors from the regression sample (Table A18), and (e) expanding the sample to all U.S. importers in Panjiva (including those not matched to Y14) (Table A19). See Appendix A-V for a detailed presentation of robustness checks.

4 Supplier Search Costs

U.S. firms responded to the 2018–2019 tariffs by terminating relationships with Chinese suppliers and looking for trade partners in other Asian countries. In this section, we provide more direct evidence on the costs of searching for new suppliers by documenting heterogeneous time to finding new suppliers by firm and product type. In particular, we explore the extent to which (a) relationship stickiness, and (b) prior experience with Asian suppliers determine the speed of matching to new suppliers.

We employ the Cox proportional hazards model and estimate the following equation:

$$\lambda_{ip}(t) = \lambda_0(t) \exp\Big[\xi X_{ip} + \rho_s + \nu_k\Big], \tag{2}$$

where $\lambda(t)$ is the expected hazard in quarter t for a given firm-product pair and $\lambda_0(t)$ is the baseline hazard. The regressor of interest is included in X_{ip} and refers to either an indicator for product-level relationship stickiness or an indicator for those importers with prior supplier ties in Asia (ex China). X_{ip} also includes firm-level covariates as in Equation 1 (size, leverage, liquidity, ROA, and retaliation tariff dummy). In addition to state (ρ_s)

and industry fixed effects (ν_k), we control for firm-level credit demand obtained using the methodology of Amiti and Weinstein (2018).[14]

Relationship Stickiness. High search costs lead to non-diversified and persistent supplier networks. Martin *et al.* (2024) construct a product-level measure of trade relationship stickiness using data on the duration of buyer-supplier relationships for over 5,000 HS6 products. Products characterized by more specificity exhibit stickier relationships and a higher cost of switching to an alternative supplier. Using this measure of trade relationship stickiness, we split firms into low- and high-stickiness relationships (around the product-level median). Columns 1-2 in Table 4 report the hazard ratios estimated based on Equation 2 by firm heterogeneity in relationship stickiness. The positive and statistically significant estimates suggest that tariff-hit firms with low-stickiness relationships are better able to find a new Asian supplier than other firms. Low-stickiness relationship firms have a hazard of matching to a new Asian supplier that is 16% to 19% higher than high-stickiness relationship firms.

Ex-ante Supplier Relationships in Asia. We define a firm as ex-ante diversified if it had at least one supplier in Asia (ex-China) during 2016–2017. Diversified firms with prior supplier ties in Asia (ex-China) have superior knowledge about the region and should face lower search costs. The results reported in Columns 3 and 4 of Table 4 are significant and economically sizable, indicating that pre-tariffs supplier relationships in Asia improve the likelihood of finding new suppliers after the tariffs. Hazard ratio estimates indicate that ex-ante diversified firms match to new suppliers about 3 times faster than other firms.

Overall, these findings align with the notion that supply chain realignment involves non-trivial search frictions. Importers facing supplier search costs would therefore benefit from external financing and information about potential supplier networks. To delve into these

[14] Following Amiti and Weinstein (2018), we collect the estimated fixed effects coefficients from a regression of loan commitment growth in the Y14 dataset on bank×quarter and firm×quarter fixed effects. This regression includes only firms with loans from at least two banks in any given quarter. Firms' fixed effects can be interpreted as firm-specific changes in demand because changes in loan volumes from any of the banks (to a given firm) must be driven by credit supply (Khwaja and Mian, 2008).

channels, we turn to the role of banks.

5 Bank Credit Demand

To analyze the role of banks in the realignment of U.S.-China supply chains, we estimate the following baseline credit regression at the (bank-firm-quarter) loan level:

$$\text{Bank Credit Outcome}_{ibt} = \delta_1 \text{Tariff-hit}_i \times \text{Post}_t + \delta_2 X_i \times \text{Post}_t + \alpha_i + \varphi_{kst} + \kappa_{bt} + \tau_{ib} + \epsilon_{ibt}, \quad (3)$$

where Bank Credit Outcome$_{ibt}$ denotes either the credit line utilization rate or the loan interest rate of firm i borrowing from bank b in quarter t. The tariff-hit dummy variable identifies "treated" firms (accounting for 15.6% of loans in the regression sample). The control group comprises importers that are not subject to tariffs and all other borrowing firms.[15] The Post dummy and the set of controls X_i are the same as in Equation 1. The specification includes firm fixed effects (α_i) to examine within-firm changes in lending outcomes following the imposition of tariffs. Industry×state×quarter fixed effects (φ_{kst}) control for time-varying industry and local shocks that are common to all firms. Bank×quarter fixed effects (κ_{bt}) absorb bank-specific shocks that might influence lending decisions. Finally, bank×firm fixed effects (τ_{ib}) control for assortative bank-firm matching (Chodorow-Reich, 2014; Schwert, 2018). All specifications are estimated using OLS and the standard errors are clustered at the firm-quarter level.

Results. The credit results are presented in Table 5 and indicate a positive and statistically significant association between firms' tariff exposure on the one hand, and credit quantities and prices on the other hand. During 2018–2019, credit line utilization rates for tariff-hit importers are 0.7 pps higher than for other firms (Column 1). For comparison, utilization rates increase by 8–10 pps following large aggregate shocks such as the 2007–2008 financial

[15] The average credit line utilization rate is 35% and the median interest rate is 3.75% (Table 1). We also estimate Equation 3 restricting the control group to importers, see Appendix A-V.

crisis and the Covid-19 pandemic (see, e.g., Acharya *et al.*, 2024; Berrospide and Meisenzahl, 2022; Chodorow-Reich *et al.*, 2022). The increase in credit line utilizations is indicative of higher credit demand because banks cannot renege on pre-committed lines of credit unless the firm breaches covenants (Sufi, 2009).

In Columns 2–3, we examine loan interest rates in the sample of outstanding loans and that of new loans, respectively. Estimates show that tariff-hit importers receive more expensive loans by 3.6 basis points (bps) (Column 2). This estimate is a lower bound on the true increase in the price of credit because rate changes in the stock of outstanding loans come from loan modifications (affecting only about 20% of loans (Bidder *et al.*, 2023)) and the origination of new loans (accounting for only 5% of all outstanding loans). Indeed, when we limit the analysis to the small sample of newly originated loans (Column 3), we estimate a much larger price effect (close to 18 bps). The joint increase of loan quantities and prices for tariff-hit firms suggests that these firms have higher credit demand during 2018–2019 than other firms, consistent with the salience of tariffs as an input cost shock.

Trade Credit. Trade credit provided by suppliers and customers along the supply chain is critical in preserving the stability of trade relationships (Niepmann and Schmidt-Eisenlohr, 2017; Ersahin *et al.*, 2024b,a). To rule out the possibility that omitting trade credit from our regressions could bias upwards the estimates for bank credit, we examine within-firm changes in trade credit in a DiD framework at the firm-year level. Our proxy for trade credit is accounts payable as a share of total revenues, which is 7.5% for the average firm (Table A2). Table A8 shows no evidence that tariff-hit firms increased their reliance on trade credit more than other firms after the enactment of the tariffs.

Robustness. The evidence of higher credit demand for tariff-hit importers is robust to a wide range of additional checks (discussed in detail in Appendix A-V), of which we highlight the most important. First, our main findings are the same using a nearest-neighbor matching estimator (Table A11). Second, placebo tests in regression samples that precede our sample period by several years show no evidence that unobservables are responsible for our main results (Table A13). Third, our results are insensitive to controlling for relationship banking with the end-2017 loan share as a measure of bank-firm relationship intensity (Table A15). Fourth, our results hold up to dropping all loans to publicly-listed firms (Table A17) or restricting the control group only to importers (Table A14).

6 Role of Specialized Banks

So far, our results show that tariff-hit U.S. importers pared back exposure to Chinese suppliers, diversified towards Asian markets outside China, and had higher credit demand during 2018–2019. The next step is to explore the role of specialized banks in mitigating financial and information frictions associated with trade search costs. We are interested in determining if tariff-hit firms borrowing from specialized banks benefited from favorable loan terms (a *credit* channel) and information about potential suppliers (*information* channel). We conclude by providing direct (reduced-form) evidence of the value of relationships with specialized banks in lessening supply chain realignment.

6.1 Measuring Bank Specialization

If banks differ in market- and industry-specific knowledge, then credit is not perfectly substitutable across banks and a relationship with a specialized lender can have important benefits. Blickle *et al.* (2023, 2024) show, theoretically and empirically, that specialized banks leverage their informational advantages in certain industries to offer cheaper loans and have better asset quality than other banks. Our analysis requires a measure of specialization that reflects banks' informational advantages in working with firms engaged in trade activities with Asian countries. This advantage is difficult to capture for trade activities because the trade finance market is highly concentrated and only a handful of U.S. banks provide specialized trade finance services. Therefore, we depart from previous studies that measure bank specialization based on loan portfolio concentration into specific industries and focus instead on bank business model exposure to trade finance services and to foreign markets.

Thus, we sort the banks in our sample on two dimensions: activity (the bank offers trade finance products, such as letters of credit, trade performance guarantees, and insurance products) and geography (the bank has knowledge of Asian markets). We operationalize the definition of a "specialized bank" by selecting banks with positive cross-border trade finance claims on corporate borrowers in Asia (ex China) during 2016–2017.[16] About 10% of the banks, accounting for one-third of total loans in the Y14 dataset, are selected as "specialized" according to this measure. As discussed below, we also check the robustness of our findings to a measure of bank specialization that requires the bank to have local offices in Asia.

Balancing Characteristics across Banks and Firms. Two potential concerns arise when we test for differential outcomes for firms with a specialized versus a non-specialized bank. First, specialized banks may be systematically different from other banks. As shown in Table A4, specialized banks are indeed slightly larger than other non-specialized banks, reflecting their global nature. However, all other characteristics—capital ratios, core deposit share, profitability, and asset quality—are statistically indistinguishable between the two types of banks. Second, the firms borrowing from specialized banks may be different from those borrowing from other banks. However, this is not the case, as the two groups of firms are similar in terms of key balance sheet characteristics and lending outcomes (Table A5).

6.2 Credit Channel

We test for differential effects in bank borrowing by tariff-hit importers using the specification in Equation 3 for loan interest rates and breaking down the DiD coefficient by specialized

[16] Cross-border trade finance claims on foreign non-financial firms arise when the U.S. parent bank makes direct cross-border loans or when the foreign subsidiaries of a U.S. bank make loans and those loans are booked on the parent banks' balance sheet. We source this information from the regulatory FFIEC 009 (Country Exposure Report/Country Exposure Information Report) form, which collects information on the distribution, by country, of claims on foreigners held by certain U.S. banks.

versus other banks. The estimates—reported in Table 6—indicate that use of revolving credit lines does not differ by bank type (Column 1). However, tariff-hit firms with specialized banks borrow at significantly lower rates compared to those with non-specialized banks (by 4.5 bps in outstanding loans and 18.5 bps in new loans), as seen in Columns 2 and 3.[17]

To address the possibility that our bank specialization measure captures the benefits of borrowing from a global bank rather than a bank specialized in Asian markets, we perform a placebo test that replaces Asian with European specialization. Here, specialized banks are defined as those banks with positive cross-border trade finance claims on European corporate borrowers (but not Asian ones) in 2016–2017. The estimates in Columns 4–6 of Table 6 confirm our prior that results reflect banks' specialization in Asian markets and not their global nature.

Robustness. Our results are robust (and in some cases become stronger) when we: (a) use a matching estimator (Table A11), (b) control for relationship banking (A15), and (c) broaden the definition of bank specialization to include all banks with local presence in Asia (Table [XX])—see Appendix A-V.

6.3 Information Channel

We document the role of specialized banks in supplying information about potential trade relationships using three approaches. First, we use information on international bank-to-firm and firm-to-firm networks to examine the odds of matching to an Asian supplier when that supplier had been a client of a U.S. bank or had done business with U.S. firms before the tariffs. Second, we reduce the role of the credit channel by testing if credit-unconstrained firms find new suppliers faster when they have a relationship with a specialized bank.[18]

[17] Exploring additional margins of lending, we find that tariff-hit firms with specialized banks receive loans with longer maturity and are assessed as having lower default risk than tariff-hit firms with other banks (Table A7, Columns 1–2). In addition, there is no evidence in loan- and bank-level data that specialized banks experience worse ex-post loan performance (Columns 3–4 of Table A7 and Table A8, respectively).

[18] As before, the baseline sample excludes multinational firms. Eliminating these firms allays the potential concern that the evidence on the information channel is driven by firms' own network effects.

Third, we compare changes in foreign subsidiary income from advisory services between Asian versus non-Asian subsidiaries of specialized banks.

Network Effects. By serving foreign markets, specialized banks have access to information about customers networks outside the U.S. To test for "network effects" in the process of matching to new Asian suppliers, we start by tracking these suppliers to determine if they were clients of a U.S. bank or if they previously exported to U.S. firms before the rise of trade tensions. More precisely, we name-match the new Asian suppliers identified during 2018–2022 with the (a) foreign borrowers from any Y14-reporting bank and (b) trade partners of any U.S. firm present in the Y14 dataset, respectively.[19]

Cox proportional hazards regressions in Table 7 evaluate the role of network effects in improving the odds of U.S. importers matching to new Asian suppliers. Estimates in Panel A are positive and statistically significant, indicating that tariff-hit U.S. importers with specialized banks are more successful in finding new Asian suppliers (by 6.4% in Column 4) compared to tariff-hit firms who borrow from other banks. Estimates in Panel B show that the odds of finding new Asian suppliers who are preexisting clients of any U.S. bank increase by 10-20% (Columns 1–2). Furthermore, matching to a new Asian supplier who was in a trade relationship with U.S. firms before the tariffs is faster by 14-21% (Columns 3–4).

Unconstrained Firms. Our second test of the *information* channel exploits firm heterogeneity in ex-ante financial constraints. To reduce the role of the credit channel, we focus on firms that are less likely to be credit constrained (to which we refer as "unconstrained"). For these firms, the value of a relationship with a specialized bank is unlikely to come from better loan terms but instead from the information the bank can provide about Asian markets. We use two proxies for financial constraints—based on firm size and risk rating at the end

[19] We are able to trace the new Asian suppliers that borrow from Y14-reporting banks due to the availability of this information in the Y14 dataset, which collects lending information to both domestic and foreign firms. However, we are unable to examine the odds of matching to a new Asian supplier who is also a borrower of a *specialized* U.S. bank, as we obtain very few matches.

of 2017—with the assumption that larger (above-median total assets) and investment grade firms (rated BBB or above) have better access to external finance (Campello *et al.*, 2010; Hadlock and Pierce, 2010; Dinlersoz *et al.*, 2018). Table 8 shows the results of estimating the Cox proportional hazards model on the sample of unconstrained firms. Across specifications, positive and statistically significant estimates indicate that unconstrained tariff-hit firms are faster in finding new Asian suppliers when borrowing from a specialized bank (Columns 1–4). In addition, we are able to rule out that these firms appear more successful because of selection into working with specialized banks (Table A6) or because they receive better loan terms from these banks (Table A10). Overall, the evidence points to an information role for specialized banks among the firms for which the credit channel is arguably less relevant.

Advisory Fees. Our third test of the information channel exploits heterogeneity in the locations of foreign subsidiaries of U.S. banks. To the extent that specialized banks leverage their informational advantages and provide consulting and advisory services to their client firms, then the information channel may be captured in the bank's income from formal advisory services. Therefore, we test if Asian subsidiaries of specialized banks exhibit stronger advisory fee income growth than non-Asian subsidiaries of a given specialized parent bank. The DiD results in quarterly subsidiary-level data are shown in Table [XX].[20] Positive and statistically significant estimates on the DiD term "Post×Asian subsidiary" in Columns 1-2 suggest that Asian subsidiaries grew fee-based income faster by [XX]% during the 2018–2019 period than subsidiaries located elsewhere. Columns 3–4 break down this coefficient by specialized parent bank. The results reveal significant effects for both specialized and other parent banks, although the coefficient estimates are larger for specialized parent banks, indicating growth of [XX]% and thus higher than that of other banks.

In conclusion, the suggestive evidence presented in this section—(a) network effects in

[20] For this test, the data are sourced from the supervisory FR 2314 (Financial Statements of Foreign Subsidiaries of U.S. Banking Organizations) form which reports quarterly balance sheet and income statement information for the foreign subsidiaries of U.S. state member banks. *Results based on the FR 2314 are pending clearance and not shown in the current draft.*

the formation of new trade relationships, (b) improved odds of forming such relationships for less credit-constrained firms, and (c) higher income growth at Asian locations of foreign subsidiaries—overall supports the notion of informational advantages at specialized banks that manifest through an "information channel" in the realignment of global supply chains.

6.4 Specialized Banks and Supply Chain Realignment

Our final tests provide direct (reduced-form) evidence for the value of relationships with specialized banks in lessening supply chain realignment. Using the baseline trade specification (Equation 1), we break down the DiD coefficients on "Tariff-hit×Post" by whether the firm is in a relationship with a specialized bank. As shown in Table 9, tariff-hit importers borrowing from specialized banks are better able to diversify suppliers outside China those those borrowing from other banks. Interpreting the coefficient estimates as marginal effects, the probability of matching to a new Asian supplier is over 15 pps higher for firms with specialized banks (Column 1) and such firms increase their import shares from Asia (ex-China) by 5.6 pps more than other firms (column 3, significant at 15%). Estimates in Columns 4-6 indicate no evidence of Europe-specialized banks improving firms' ability to establish new trade relationships in Asia. We subject these results to several of our previous robustness checks, as discussed in Appendix A-V.

Economic Evaluation of the Search Cost. We conduct a back-of-the-envelope calculation to gauge the search cost (in $ terms) incurred by the average importer in our sample during their search for new Asian suppliers. Using the DiD coefficient that indicates a credit line utilization rate increase of 0.7 pps during the escalation of trade tensions (Column 1, Table 5), coupled with the average utilization rate (34.6%), credit line commitment ($25.3 mn), and time it takes a firm to match with a new Asian supplier (10.7 quarters), we obtain an estimate of $(34.6\% + 0.7\%) \times \$25.3 \times 10.7 = \$1.9$ mn, or the equivalent of 5% of annual sales revenue for the average tariff-hit importer.

How much does a relationship with a specialized bank reduce this cost? According to the estimates in Panel A of Table 7, the difference in hazard ratios between firms with and without specialized banks ranges between 4.2% and 10%. Given that the average time it takes a firm to match with a new Asian supplier is 10.7 quarters, it is between $4.2\% \times 10.7 \times 3 = 1.3$ months and $10\% \times 10.7 \times 3 = 3.2$ months relatively faster for firms with specialized banks to connect to Asian suppliers.

7 Conclusions

In this paper, we exploit the "great reallocation" of global supply chains induced by the 2018–2019 U.S.-China tariffs to study the relationship between trade search costs and financial frictions. For this purpose, we bring together two large datasets with detailed information on imports and bank loan contracts for (mostly private and bank-dependent) U.S. non-financial firms. These data allow us to track importer-to-supplier relationships across countries and to examine the role of banks in the realignment of global supply chains.

Our analysis offers three novel insights. *First*, in reallocating their sourcing from Chinese suppliers to other Asian countries, U.S. importers face salient search costs. The estimated cost of matching to a new Asian supplier for the average importer subject to the tariffs is \$1.9 million (or 5% of annual sales revenue). *Second*, in response to the tariff-induced input cost shock, U.S. importers increased their demand for bank credit, drawing more heavily on credit lines and taking out loans at higher rates. *Third*, specialized banks with expertise in trade finance services to Asian markets played a key role in easing financial and information frictions. The evidence suggests that tariff-hit importers borrowing from specialized banks benefited not only from cheaper credit, but also from information about supplier networks, which helped them form new trade relationships faster.

Our results emphasize the importance of banks, especially specialized banks, in absorbing supply chain shocks and their macroeconomic consequences. Our findings also provide an explanation for the relative speed with which the "great reallocation" of global value chains appears to have occurred in the wake of the 2018–2019 tariffs.

References

Abadie, A. and Imbens, G. W. (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics*, **29** (1), 1–11.

Acemoglu, D. and Tahbaz-Salehi, A. (2024). The Macroeconomics of Supply Chain Disruptions. *Review of Economic Studies*, **forthcoming**.

Acharya, V. V., Jager, M. and Steffen, S. (2024). Contingent credit under stress. *Annual Review of Financial Economics*, **16**, 343–365.

Alessandria, G., Arkolakis, C. and Ruhl, K. J. (2021). Firm dynamics and trade. *Annual Review of Economics*, **13**, 253–280.

—, Khan, S. Y., Khederlarian, A., Mix, C. and Ruhl, K. J. (2023). The aggregate effects of global and local supply chain disruptions: 2020–2022. *Journal of International Economics*, **146**, 103788.

Alessandria, G. A., Khan, S. Y., Khederlarian, A., Ruhl, K. J. and Steinberg, J. B. (2024). Trade War and Peace: U.S.-China Trade and Tariff Risk from 2015–2050. *NBER Working Paper No. 32150*.

Alfaro, L. and Chor, D. (2023). Global Supply Chains: The Looming "Great Reallocation". *NBER Working Paper No. 31661*.

—, —, Antras, P. and Conconi, P. (2019). Internalizing global value chains: A firm-level analysis. *Journal of Political Economy*, **127** (2), 508–559.

Allen, T. (2014). Information frictions in trade. *Econometrica*, **82** (6), 2041–2083.

Amiti, M. and Weinstein, D. E. (2011). Exports and financial shocks. *Quarterly Journal of Economics*, **126** (4), 1841–1877.

— and — (2018). How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data. *Journal of Political Economy*, **126** (2), 525–587.

Antràs, P., Fadeev, E., Fort, T. C. and Tintelnot, F. (2024). Exporting, global sourcing, and multinational activity: Theory and evidence from the United States. *Review of Economics and Statistics*, **forthcoming**.

Antras, P. and Foley, C. F. (2015). Poultry in motion: A study of international trade finance practices. *Journal of Political Economy*, **123** (4), 853–901.

—, Fort, T. C. and Tintelnot, F. (2017). The margins of global sourcing: Theory and evidence from US firms. *American Economic Review*, **107** (9), 2514–2564.

Autor, D., Beck, A., Dorn, D. and Hanson, G. (2024). Help for the heartland? The employment and electoral effects of the Trump tariffs in the United States. *NBER Working Paper No.32082*.

Bai, X., Fernández-Villaverde, J., Li, Y. and Zanetti, F. (2024). The causal effects of global supply chain disruptions on macroeconomic outcomes: Evidence and theory. *NBER Working Paper No. 32098*.

Baldwin, R., Freeman, R. and Theodorakopoulos, A. (2023). Hidden exposure: Measuring U.S. supply chain reliance. *NBER Working Paper No. 31820*.

Benguria, F. and Saffie, F. (2024). Escaping the trade war: Finance and relational supply chains in the adjustment to trade policy shocks. *Journal of International Economics*, **152**, 103987.

Berger, A. N., Pinzon Puerto, F. A., Karlström, P. and Ossandon Busch, M. (2023). Trade disruptions and global banking. *Available at SSRN 4660067*.

Berrospide, J. M. and Meisenzahl, R. (2022). The real effects of credit line drawdowns. *International Journal of Central Banking*, **18** (3), 321–397.

Berthou, A., Mayer, T. and Mésonnier, J.-S. (2024). Good connections: Bank specialization and the tariff elasticity of exports. *Journal of International Economics*, **152**, 104021.

Bidder, R. M., Crouzet, N., Jacobson, M. M. and Siemer, M. (2023). *Debt Flexibility*. Finance and Economics Discussion Series 2023-076, Board of Governors of the Federal Reserve System (U.S.).

Blickle, K., He, Z., Huang, J. and Parlatore, C. (2024). Information-based pricing in specialized lending. *NBER Working Paper No. 32155*.

—, Parlatore, C. and Saunders, A. (2023). Specialization in banking. *Journal of Finance*, **forthcoming**.

Bown, C. P. (2021). The U.S.–China trade war and Phase One agreement. *Journal of Policy Modeling*, **43** (4), 805–843.

Brancati, E. (2022). Help in a Foreign Land: Internationalized Banks and Firms' Export. *Available at SSRN 4154365*.

Bronzini, R. and D'Ignazio, A. (2017). Bank internationalization and firm exports: Evidence from matched firm–bank data. *Review of International Economics*, **25** (3), 476–499.

Caliendo, L. and Parro, F. (2023). Lessons from U.S.–China trade relations. *Annual Review of Economics*, **15** (1), 513–547.

Campello, M., Graham, J. R. and Harvey, C. R. (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics*, **97** (3), 470–487.

Chaney, T. (2016). Liquidity constrained exporters. *Journal of Economic Dynamics and Control*, **72**, 141–154.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008-9 financial crisis. *Quarterly Journal of Economics*, **129** (1), 1–59.

—, Darmouni, O., Luck, S. and Plosser, M. (2022). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics*, **144** (3), 908–932.

Chor, D. and Manova, K. (2012). Off the cliff and back? Credit conditions and international trade during the global financial crisis. *Journal of International Economics*, **87** (1), 117–133.

Claessens, S. and Van Horen, N. (2021). Foreign banks and trade. *Journal of Financial Intermediation*, **45**, 100856.

Di Giovanni, J., Kalemli-Özcan, S., Silva, A. and Yildirim, M. A. (2023). Pandemic-era inflation drivers and global spillovers. *NBER Working Paper No. 31887*.

—, Levchenko, A. A. and Mejean, I. (2014). Firms, destinations, and aggregate fluctuations. *Econometrica*, **82** (4), 1303–1340.

—, — and — (2018). The micro origins of international business-cycle comovement. *American Economic Review*, **108** (1), 82–108.

—, — and — (2024). Foreign shocks as granular fluctuations. *Journal of Political Economy*, **132** (2), 391–433.

Dinlersoz, E. M., Kalemli-Özcan, S., Hyatt, H. R. and Penciakova, V. (2018). Leverage over the firm life cycle, firm growth, and aggregate fluctuations. *NBER Working Paper No. 25226*.

Elsas, R. (2005). Empirical determinants of relationship lending. *Journal of Financial Intermediation*, **14** (1), 32–57.

Ersahin, N., Giannetti, M. and Huang, R. (2024a). Supply chain risk: Changes in supplier composition and vertical integration. *Journal of International Economics*, **147**, 103854.

—, — and — (2024b). Trade credit and the stability of supply chains. *Journal of Financial Economics*, **155**, 103830.

Fajgelbaum, P., Goldberg, P. K., Kennedy, P. J., Khandelwal, A. and Taglioni, D. (2024). The U.S.-China Trade War and Global Reallocations. *American Economic Review: Insights*, **6** (2), 295–312.

Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J. and Khandelwal, A. K. (2020). The return to protectionism. *Quarterly Journal of Economics*, **135** (1), 1–55.

— and Khandelwal, A. K. (2022). The economic impacts of the U.S.–China trade war. *Annual Review of Economics*, **14**, 205–228.

Favara, G., Ivanov, I. and Rezende, M. (2021). GSIB surcharges and bank lending: Evidence from U.S. corporate loan data. *Journal of Financial Economics*, **142** (3), 1426–1443.

Federico, S., Hassan, F. and Rappoport, V. (2023). Trade Shocks and Credit Reallocation. *NBER Working Paper No. 31111.*

Flaaen, A., Haberkorn, F., Lewis, L., Monken, A., Pierce, J., Rhodes, R. and Yi, M. (2023). Bill of lading data in international trade research with an application to the COVID-19 pandemic. *Review of International Economics*, **31** (3), 1146–1172.

Foley, C. F. and Manova, K. (2015). International trade, multinational activity, and corporate finance. *Annual Review of Economics*, **7** (1), 119–146.

Fontaine, F., Martin, J. and Mejean, I. (2023). Frictions and adjustments in firm-to-firm trade. *CEPR Discussion Paper No. DP18110.*

Freund, C., Mattoo, A., Mulabdic, A. and Ruta, M. (2024). Is U.S. trade policy reshaping global supply chains? *Journal of International Economics*, **152**, 104011.

Gaubert, C. and Itskhoki, O. (2021). Granular Comparative Advantage. *Journal of Political Economy*, **129** (3), 871–939.

Goldberg, P. K. and Reed, T. (2023). Is the Global Economy Deglobalizing? And if so, why? And what is next? *NBER Working Paper No. 31115.*

Gopinath, G., Gourinchas, P.-O., Presbitero, A. F. and Topalova, P. (2025). Changing Global Linkages: A New Cold War? *Journal of International Economics*, **153**, 104042.

Grossman, G., Helpman, E. and Redding, S. (2024). When tariffs disrupt global supply chains. *American Economic Review*, **114** (4), 988–1029.

Hadlock, C. J. and Pierce, J. R. (2010). New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *Review of Financial Studies*, **23** (5), 1909–1940.

Handley, K., Kamal, F. and Monarch, R. (2024). Rising import tariffs, falling export growth: When modern supply chains meet old-style protectionism. *American Economic Journal: Applied Economics*, **forthcoming**.

Imbens, G. W. and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, **47** (1), 5–86.

Kabir, P., Matray, A., Müller, K. and Xu, C. (2024). EXIM's Exit: The Real Effects of Trade Financing by Export Credit Agencies. *NBER Working Paper No. 32019.*

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, **98** (4), 1413–1442.

Klein, M. W., Peek, J. and Rosengren, E. S. (2002). Troubled banks, impaired foreign direct investment: The role of relative access to credit. *American Economic Review*, **92** (3), 664–682.

Kramarz, F., Martin, J. and Mejean, I. (2020). Volatility in the small and in the large: The lack of diversification in international trade. *Journal of International Economics*, **122**, 103276.

Kysucky, V. and Norden, L. (2016). The benefits of relationship lending in a cross-country context: A meta-analysis. *Management Science*, **62** (1), 90–110.

Manova, K. (2012). Credit Constraints, Heterogeneous Firms, and International Trade. *Review of Economic Studies*, **80** (2), 711–744.

Martin, J., Mejean, I. and Parenti, M. (2024). Relationship stickiness, international trade, and economic uncertainty. *Review of Economics and Statistics*, **forthcoming**, 1–45.

Michalski, T. and Ors, E. (2012). (Interstate) Banking and (interstate) trade: Does real integration follow financial integration? *Journal of Financial Economics*, **104** (1), 89–117.

Minetti, R., Murro, P., Rotondi, Z. and Zhu, S. C. (2019). Financial constraints, firms' supply chains, and internationalization. *Journal of the European Economic Association*, **17** (2), 327–375.

Monarch, R. (2022). "It's Not You, It's Me": Prices, Quality, and Switching in US-China Trade Relationships. *Review of Economics and Statistics*, **104** (5), 909–928.

— and Schmidt-Eisenlohr, T. (2023). Longevity and the value of trade relationships. *Journal of International Economics*, **145**, 103842.

Niepmann, F. and Schmidt-Eisenlohr, T. (2017). International trade, risk and the role of banks. *Journal of International Economics*, **107**, 111–126.

Paravisini, D., Rappoport, V. and Schnabl, P. (2023). Specialization in Bank Lending: Evidence from Exporting Firms. *Journal of Finance*, **78** (4), 2049–2085.

Schwert, M. (2018). Bank capital and lending relationships. *Journal of Finance*, **73** (2), 787–830.

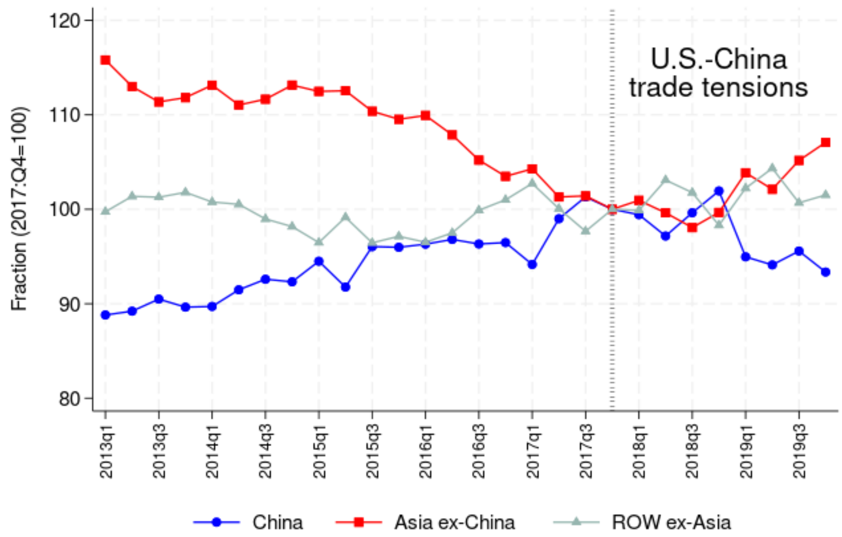
Silva, J. S. and Tenreyro, S. (2006). The Log of Gravity. *Review of Economics and Statistics*, **88** (4), 641–658.

Sufi, A. (2009). Bank lines of credit in corporate finance: An empirical analysis. *Review of Financial Studies*, **22** (3), 1057–1088.

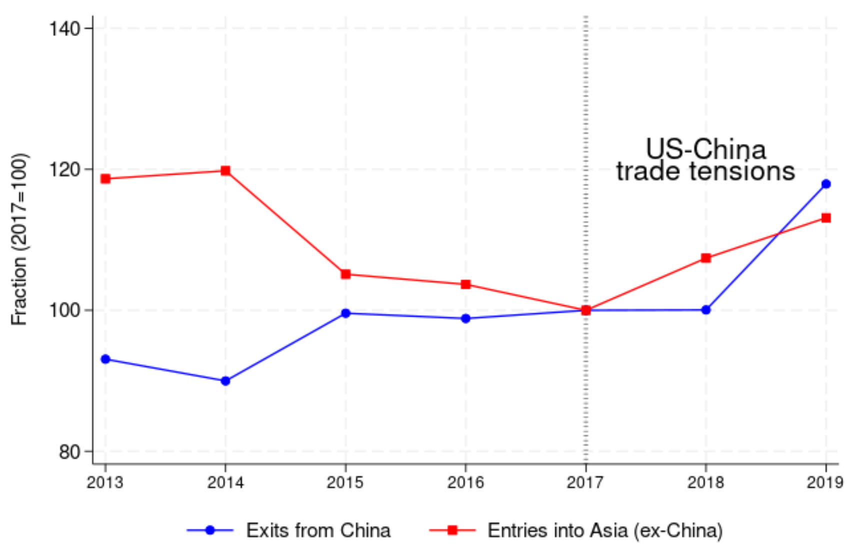
UNCTAD (2021). Review of Maritime Transport 2021. United Nations Conference on Trade and Development, Geneva.

Figure 1: **Supply chain reconfiguration and U.S.-China trade tensions**

This figure plots, for U.S. importers, the average (a) quarterly share of imports from China, Asia and the rest of the world (ROW), (b) number of supplier exits from China and number of supplier entries into Asia (excluding China). The figures are based on data from approximately 45 million shipments to 1.1 million importing firms that arrived in the U.S. during 2013:Q1-2019:Q4. Source: Authors' calculations using data from S&P Panjiva Supply Chain Intelligence.



(a) Share of import volumes



(b) Supplier exits from China and entries to Asia (ex-China)

Table 1: **Descriptive statistics**

This table shows descriptive statistics for the main variables in the regression samples over the 2016–2019 period. Panels A–B report summary statistics for the main variables in the trade regressions and bank credit regressions. Panel C reports summary statistics for the main variables in the information channel regressions for foreign bank subsidiaries. Sources: Authors' calculations using data from S&P Panjiva Supply Chain Intelligence, FR Y-14Q, and FR 2314.

Variable	(1) **Obs.**	(2) **Mean**	(3) **St. Dev.**	(4) **P25**	(5) **Median**	(6) **P75**
(A) Firm-product-year data						
Tariff-hit firm	151437	0.424	0.494	0.000	0.000	1.000
Unconditional:						
0/1 Exit from China	151437	0.448	0.497	0.000	0.000	1.000
# Chinese suppliers lost	151437	0.625	1.156	0.000	0.000	1.000
Import share - China	151437	0.452	0.481	0.000	0.026	1.000
0/1 Entry in Asia (ex-China)	151437	0.114	0.317	0.000	0.000	0.000
# Asian suppliers gained	151437	0.197	0.871	0.000	0.000	0.000
Import share - Asia (ex-China)	151437	0.103	0.277	0.000	0.000	0.000
Conditional on positive values:						
# suppliers China (total)	79175	1.666	2.072	1.000	1.000	2.000
# suppliers Asia (ex-China) (total)	25250	2.229	3.293	1.000	1.000	2.000
# suppliers ROW	6664	2.055	4.726	1.000	1.000	2.000
(B) Loan-level data						
Tariffs-hit firm	895973	0.081	0.273	0.000	0.000	0.000
0/1 Bank is specialized - Asia	895973	0.329	0.470	0.000	0.000	1.000
0/1 Bank is specialized - Europe	615768	0.311	0.463	0.000	0.000	1.000
Credit line utilization rate	775974	0.346	0.366	0.000	0.233	0.662
Interest rate (pps) - all loans	895973	3.719	1.489	2.887	3.732	4.520
Interest rate (pps) - new loans	15323	3.885	1.319	3.024	3.750	4.500
Firm size (log-assets)	895973	18.506	2.480	16.609	18.182	20.263
Firm cash ratio (cash/assets)	895973	0.086	0.123	0.011	0.041	0.112
Firm leverage (debt/assets)	895973	0.405	0.275	0.210	0.370	0.559
Firm return on assets (ROA)	895973	0.155	0.197	0.062	0.120	0.194
0/1 Firm with retaliatory tariffs	895973	0.005	0.072	0.000	0.000	0.000
0/1 Firm with specialized bank	1439709	0.276	0.447	0.000	0.000	1.000
0/1 Firm with low-stickiness relationship	1588384	0.357	0.479	0.000	0.000	1.000
0/1 Firm with prior suppliers in Asia	1687717	0.849	0.358	1.000	1.000	1.000

Table 2: **Firm-level within-product diversification**

This table reports firm-level statistics on the number of source countries and individual suppliers from which U.S. firms imported a given 6-digit HS product in 2016 and 2022. Mean, median, and maximum values in columns are calculated across products within a given firm in a given year. Based on the distributions of these statistics across firms, mean, median, and 95th percentile values in rows are then calculated based on variation across firms in a given year. Source: Authors' calculations using data from S&P Panjiva Supply Chain Intelligence.

	(1)	(2)	(3)	(4)
Variable	**Year**	**Mean**	**Median**	**Max**
	(A) Number of source countries			
Mean	2016	1.37	1.38	1.66
	2022	1.25	1.25	1.46
Median	2016	1.00	1.00	1.00
	2022	1.00	1.00	1.00
95th percentile	2016	2.86	3.00	4.00
	2022	2.40	3.00	3.00
	(B) Number of suppliers			
Mean	2016	2.26	2.34	3.05
	2022	2.00	2.07	2.62
Median	2016	1.00	1.00	1.00
	2022	1.00	1.00	1.00
95th percentile	2016	6.64	7.00	10.00
	2022	5.48	6.00	8.00

Table 3: **Firm-level supply chain realignment**

This table reports Poisson Pseudo Maximum Likelihood (PPML) estimates from a regression of trade outcomes on tariff-hit dummy variable interacted with the Post dummy, as shown in Equation 1. The dependent variables are the probability of exit from China or entry into Asia excluding China, the number of lost Chinese suppliers and those gained in Asia (ex-China) and the import shares (based on shipment volumes for single-product shipments), by region. The data are at the firm-product-year level during 2016–2019. The sample includes all the Panjiva-Y14 matched U.S. importing firms (excluding firms importing from their affiliates abroad). Tariff-hit dummy takes value 1 for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. Post is a dummy that takes value one during 2018–2019 and zero during 2016–2017. Firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA), all measured at end-2017, and a dummy for those firms whose exports were subject to retaliatory tariffs. Industry refers to 3-digit NAICS classification. Product refers to HS6 code. Semi-elasticities are calculated as $[\exp(\beta_1) - 1] \times 100$. Standard errors are double clustered at the firm and product level. *** 1%, **5%, *10%.

Dependent variables:	(1) **0/1 Exit from China**	(2) **# Chinese suppliers lost**	(3) **Import share China**	(4) **0/1 Entry into Asia**	(5) **# Asian suppliers gained**	(6) **Import share Asia**
	(A) Realignment from China			**(B) Realignment to Asia (ex-China)**		
Tariff-hit × Post	0.5988***	0.5832***	-1.9357***	0.6433***	0.5619***	0.3890***
	(0.1172)	(0.1565)	(0.2552)	(0.0313)	(0.0366)	(0.0208)
Semi-elasticity (%)	82.0	79.2	-85.6	90.3	75.4	47.6
Observations	151,437	151,437	159,073	122,543	122,543	126,803
Firm controls × Post	Y	Y	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	Y
Product × Year FE	Y	Y	Y	Y	Y	Y
Product × Firm FE	Y	Y	Y	Y	Y	Y

Table 4: **Supplier search costs**

This table reports Cox proportional hazards model estimates based on Equation 2. The data are at the firm-product-quarter level over 2018–2022. The dependent variable represents the odds for a tariff-hit firm of finding a new supplier in Asia (ex-China). Tariff-hit dummy takes value 1 for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. "0/1 Firm with low-stickines relationships" is a dummy for firms importing a product with below-median value of relationship stickiness index from Martin *et al.* (2024). "0/1 Firm with prior suppliers in Asia" is a dummy for those firms that have at least one Asian supplier during 2010–2017. In Columns 1 and 3, firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA), all measured at end-2017, and a dummy for firms with exports subject to retaliatory tariffs. Specifications in Columns 2 and 4 also include a control for firm-level credit demand calculated following Amiti and Weinstein (2018). Industry refers to 3-digit NAICS classification. Product refers to HS6 code. Standard errors are clustered on firm-product. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Odds of finding a new Asian supplier**			
0/1 Firm with low-stickiness relationships	1.1880***	1.1588***		
	(0.0074)	(0.0100)		
0/1 Firm with prior suppliers in Asia			2.9173***	3.0928***
			(0.0607)	(0.1049)
Observations	1,547,341	831,560	1,644,339	884,957
Firm controls	Y	Y	Y	Y
Firm credit demand	-	Y	-	Y
State FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 5: **Increase in bank credit demand**

This table reports OLS estimates from a regression of lending outcomes on the tariff-hit dummy interacted with the Post dummy, as shown in Equation 3. The data are at the loan level over 2016:Q1-2019:Q4. The dependent variables are: credit line utilization defined as the ratio between the total utilized amount and the total commitment, and the loan interest rate on outstanding loans and on new loans. Tariff-hit dummy takes value one for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. The Post dummy takes value zero during 2016–2017 and one during 2018–2019. Firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA) (measured at end-2017), and a dummy for firms with exports subject to retaliatory tariffs. Industry refers to 3-digit NAICS classification. Standard errors are clustered by firm-quarter. *** 1%, **5%, *10%, #15%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **Loan interest rate**
	All loans		**New loans**
Tariff-hit × Post	0.0071***	0.0360***	0.1770#
	(0.0021)	(0.0076)	(0.1130)
Observations	775,974	890,517	15,323
R-squared	0.7586	0.8079	0.9222
Firm controls × Post	Y	Y	Y
State × Industry × Quarter FE	Y	Y	Y
Bank × Quarter FE	Y	Y	Y
Bank × Firm FE	Y	Y	Y

Table 6: **The credit channel of specialized banks**

This table reports OLS estimates from a regression of lending outcomes on the tariff-hit dummy interacted with the Post dummy, with main DiD coefficient on "Tariff-hit×Post" estimated separately for loans from specialized banks versus other banks using a spline term (there is no omitted category). "Specialized bank" is a dummy for banks with positive cross-border trade claims on nonfinancial firms in Asia (ex-China). The data are at the loan level during 2016–2019. Tariff-hit dummy takes value 1 for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. Post is a dummy that takes value one during 2018–2019 and zero during 2016–2017. Firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA) (measured at end-2017), and a dummy for firms with exports subject to retaliatory tariffs. Industry refers to 3-digit NAICS classification. Standard errors are double clustered by firm-quarter and bank. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Credit line utilization**	**Loan interest rate**	**Loan interest rate**	**Credit line utilization**	**Loan interest rate**	**Loan interest rate**
	All loans		**New loans**	**All loans**		**New loans**
	(A) Baseline: Asia specialization			**(B) Placebo: Europe specialization**		
Tariff-hit × Post × Specialized Bank [1]	0.0065**	0.0180	0.1052	0.0068	0.0693**	-0.1927
	(0.0028)	(0.0207)	(0.3941)	(0.0043)	(0.0284)	(0.1185)
Tariff-hit × Post × Other Bank [2]	0.0074**	0.0458***	0.1850*	0.0070**	0.0243	-0.0311
	(0.0037)	(0.0166)	(0.1077)	(0.0033)	(0.0169)	(0.2581)
Observations	775,974	890,517	15,323	588,861	609,771	7,711
R-squared	0.7586	0.8079	0.9222	0.7775	0.8253	0.9271
p-value t-test Ha: $\|1\| > \|2\|$	0.403	-	-	-	-	-
p-value t-test Ha: $\|1\| \neq \|2\|$	-	-	-	0.957	0.200	0.201
Firm controls × Post	Y	Y	Y	Y	Y	Y
State × Industry × Quarter FE	Y	Y	Y	Y	Y	Y
Bank × Quarter FE	Y	Y	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y	Y	Y

Table 7: **The information channel of specialized banks: Network effects**

This table reports Cox proportional hazards model estimates based on Equation 2. The data are at the firm-product-quarter level over 2018–2022. In the top panel, the dependent variable represents the odds for a tariff-hit firm of finding a new supplier in Asia (ex-China). In the bottom panel, the dependent variables represent the odds for a tariff-hit firm of finding a new supplier in Asia (ex-China) who is (i) a preexisting client of any U.S. bank (Columns 1-2); (ii) a preexisting supplier to any U.S. firm (Column 3-4). A supplier who is a preexisting client of any U.S. bank is an Asian supplier with an outstanding loan from any U.S. bank during 2016–2017. A preexisting supplier is an Asian supplier who exported to U.S. firms between 2010 and 2017. Tariff-hit dummy takes value 1 for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. The dependent variable is a dummy for a firm being linked to a specialized bank, defined as banks that offer cross-border trade financing services to nonfinancial firms in Asia (ex-China). In Columns 1 and 3, firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA), all measured at end-2017, and a dummy for firms with exports subject to retaliatory tariffs. Specifications in Columns 2 and 4 also include a control for firm-level credit demand calculated based on the Amiti and Weinstein (2018) method. Industry refers to 3-digit NAICS classification. Product refers to HS6 code. Standard errors are clustered on firm-product. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**(A) Odds of finding new supplier in Asia**			
0/1 Firm with Specialized Bank	1.0746***	1.0998***	1.0420**	1.0644***
	(0.0175)	(0.0227)	(0.0174)	(0.0240)
Observations	1,439,709	831,765	1,410,811	831,765
Firm controls	-	Y	Y	Y
Firm credit demand	-	Y	-	Y
State FE	-	-	Y	Y
Industry FE	-	-	Y	Y
Dependent variable:	**(B) Odds of finding a new Asian supplier . . .**			
	. . . which is a previous client of a U.S. bank		**. . . which is a previous supplier to U.S. firms**	
0/1 Firm with Specialized Bank	1.1001**	1.2025***	1.1440***	1.2158***
	(0.0444)	(0.0637)	(0.0541)	(0.0756)
Observations	440,447	216,592	459,659	225,229
Firm controls	Y	Y	Y	Y
Firm credit demand	-	Y	-	Y
State FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 8: **The information channel of specialized banks: Unconstrained firms**

This table reports Cox proportional hazards model estimates as in Equation 2. The data are at the firm-product-quarter level over 2018–2022. The dependent variable represents the odds for a financially unconstrained tariff-hit firm of finding a new supplier in Asia (ex-China).Tariff-hit dummy takes value 1 for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. The explanatory variable is a dummy for firms in a relationship with specialized banks, defined as those banks that have positive cross-border trade finance claims on nonfinancial firms in Asia (ex-China). The sample includes financially unconstrained firms, defined as (A) large firms with above-median total assets at end-2017 (Column 1-2); or (B) investment-grade firms (with credit rating of BBB or above) (Column 3-4). In Columns 1 and 3, firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA), all measured at end-2017, and a dummy for firms with exports subject to retaliatory tariffs. Specifications in Columns 2 and 4 also include a control for firm-level credit demand calculated following Amiti and Weinstein (2018). Industry refers to 3-digit NAICS classification. Product refers to HS6 code. Standard errors are clustered on firm-product. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Odds of finding a new Asian supplier**			
	(A) Large firms (assets > median)		**(B) Investment grade firms** (rating > BBB)	
0/1 Firm with Specialized Bank	1.1164***	1.1261***	1.1034***	1.1774***
	(0.0265)	(0.0336)	(0.0323)	(0.0452)
Observations	717,096	463,941	489,510	310,049
Firm controls	Y	Y	Y	Y
Firm credit demand	-	Y	-	Y
State FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 9: **Supply chain realignment and specialized banks**

This table reports Poisson Pseudo Maximum Likelihood (PPML) estimates from a regression of trade outcomes on China tariff-hit dummy variable interacted with the Post dummy, with main DiD coefficient on "Tariff-hit × Post" estimated separately for specialized banks versus other banks using a spline term. The dependent variables are the probability of exit from China or entry into Asia excluding China, the number of lost Chinese suppliers and gained Asian suppliers and the import shares by region (based on shipment volumes for single-product shipments). The data are at the firm-product-year level during 2016–2019. Tariff-hit dummy takes value 1 for firms importing at least one product from China during 2016–2017 that was subject to tariffs during 2018–2019. Post is a dummy that takes value one during 2018–2019 and zero during 2016–2017. All specifications, variable definitions and controls are as in Table 3. Differences between estimates for specialized and other banks is calculated as differences in semi-elasticities $[\exp(\beta_1) - 1] \times 100$. Standard errors are double clustered by firm-quarter and bank. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**0/1 Entry into Asia**	**# Asian suppliers gained**	**Asian import share**	**0/1 Entry into Asia**	**# Asian suppliers gained**	**Asian import share**
	(A) Baseline: Asia specialization			**(B) Placebo: Europe specialization**		
Tariff-hit × Post × ...						
...× 0/1 Firm with Specialized Bank [1]	0.6895***	0.6205***	0.4191***	0.5732***	0.4612***	0.3733***
	(0.1631)	(0.1789)	(0.0952)	(0.1526)	(0.1526)	(0.0924)
...× 0/1 Firm with Other Bank [2]	0.6104***	0.5187***	0.3817***	0.6746***	0.6091***	0.4046***
	(0.1511)	(0.1627)	(0.0927)	(0.1560)	(0.1785)	(0.0946)
Diff. specialized - other (ppt)	15.2	18.0	5.6	-	-	-
Observations	101,290	101,290	105,881	101,290	101,290	105,881
p-value t-test Ha: $\|1\| > \|2\|$	0.026	0.077	0.147	-	-	-
p-value t-test Ha: $\|1\| \neq \|2\|$				0.00774	0.0227	0.345
Firm controls × Post	Y	Y	Y	Y	Y	Y
State × Industry × Quarter FE	Y	Y	Y	Y	Y	Y
Bank × Quarter FE	Y	Y	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y	Y	Y

Internet Appendix for "Bank Financing of Global Supply Chains"

Laura Alfaro, Mariya Brussevich, Camelia Minoiu, Andrea Presbitero

December 30, 2024

A-I Theoretical Framework

This section outlines a simple theoretical framework that underpins our empirical analysis. This framework incorporates: i) a fixed cost of setting up a new supplier relationship in a given market and ii) banks specialized in that market, which can offer better loan terms. In this framework, supply chain realignment increases with tariffs and specialized lenders can lower the cost of matching to new suppliers.

Setup. Consider a final goods producer that imports an intermediate input from a supplier in region j at price p_j inclusive of an import tariff $\tau_j \geq 1$: $p_j = \hat{p}_j \tau_j$ (product and supplier identifiers are omitted). In period t, each importer receives a supplier-specific profit shock $\epsilon_{j,t}$ with extreme value distribution. The importer learns the value of idiosyncratic shocks for all potential suppliers and decides whether to remain in a current relationship or to switch. The importer can switch to another supplier k, in which case it receives the idiosyncratic profit shock $\epsilon_{k,t}$.

The process of switching between suppliers of a given product is costly. The fixed cost of switching $C_{j,t}$ is strictly positive. Importers learn of a price $p_{j,t}$ and decide whether to buy from a supplier at that price or search for a different supplier. Define $G(p_k)$ to be the cumulative distribution function of prices inclusive of tariffs that the importer draws the prices from when searching for a new supplier. Importer's decision to switch suppliers thus depends on the distribution of prices and profit shocks, both of which are observable to the importer, as well as the fixed cost of switching. Then the value function of an importer is given by:

$$V(p_{j,t}) = \max_k \pi(p_{j,t}) + \beta \mathbb{E}[V(p_{j,t+1})] + \mathbb{E}_\epsilon \underbrace{\left[\epsilon_{k,t} + \beta \int_{p_k^{min}}^{p_k^{max}} [V(p_{k,t+1}) - V(p_{j,t+1}) - C_{k,t}] dG(p_k) \right]}_{\text{expected value of switching suppliers}}, \tag{4}$$

where $\pi(p_j)$ represents instantaneous profits from the match and $V(p_j)$ represents the value of the match. Profits decrease in input prices: $\pi'(p_j) < 0$. β is a discount factor. The importer switches to a new supplier in region k if the value of the new match $V(p_k)$ exceeds the value of the current match $V(p_j)$ and this difference compensates the switching cost. The optimal switching policy is then defined by p_k^{max}: $V(p_k^{max}) - V(p_j) = C_k$. The switching cost captures the costs associated with gathering information about a supplier market in a given region (e.g., traveling to potential supplier's headquarters, identifying alternative shipping routes, etc.) and other sunk transactional costs (e.g., legal and consulting fees).

Bank Financing of Switching Costs. Each importer is randomly matched to a bank specialized in region j with some probability $\delta \leq 1$. The switching cost C_j can be financed by raising capital from a bank. The cost of raising capital depends on the type of a bank: $r_j \geq 1$ is a cost of capital charged by a bank specialized in region j. It includes the interest rate as well as advisory fees, i.e., payment for providing information about potential suppliers in a region. Following Blickle, He, Huang and Parlatore (2024), we assume that banks specialized in region j offer lower financing and advisory costs for firms switching to this region than to a region k. Given bank's familiarity with region j, the specialized lender offers a relatively lower interest rate to importers switching to suppliers in this region. In addition, the specialized lender can provide information about this market, which ultimately lowers the cost of switching. Thus, the switching cost, C_j, includes the cost of raising capital F_j varying by the type of bank to which the importer is matched:

$$\mathbb{E}(C_j) = \delta r_j F_j + (1-\delta) r_k F_j, \tag{5}$$

where $r_j < r_k$.

Probability of Switching. Assuming conditional independence between prices and profit shocks and using the assumption of the Type I Extreme Value distribution of the profit shocks ϵ_t, the probability of switching between suppliers j and k can be written as a conditional choice probability $\lambda_{jk,t}$ of the following form:

$$\lambda_{jk,t} = \frac{\exp[\mathbb{E}(V(p_{k,t+1}) - V(p_{j,t+1}) - C_{k,t})]}{\sum_{j',k'} \exp[\mathbb{E}(V(p_{k',t+1}) - V(p_{j',t+1}) - C_{k',t})]}. \tag{6}$$

This expression aligns with the conditional choice probability function derived by Monarch (2022) (see proof of Proposition I).

Testable Predictions. Using the conditional choice probability function in Equation 6, we can derive two testable predictions that we can take to the data.

First, it is straightforward to show that, if the value of a current supplier match declines in price, the probability of switching to a new supplier increases with tariffs $\tau_{j,t}$:

$$\frac{\partial \lambda_{jk,t}}{\partial \tau_{j,t}} > 0. \tag{7}$$

This first prediction underpins the empirical specifications in Section 3, where we examine the effects of importer exposure to tariffs on several trade outcomes, including the probability of establishing new supplier relationship outside China and the number of new suppliers.

In addition, given that the probability of switching is decreasing in switching costs $C_{k,t}$, we have:

$$\frac{\partial \lambda_{jk,t}}{\partial r_k} < 0. \tag{8}$$

Thus, the probability of switching to a supplier in region k declines with the cost of financing offered by banks specialized in this region. This second prediction forms the basis for the empirical tests in Section 6.4, where we examine the effects of a firm's relationship with specialized banks on trade outcomes (e.g., the probability of establishing a new supplier relationship, the number of new suppliers, and the import share in the new market.)

A-II Data Appendix

In this appendix we describe the matching between the S&P Panjiva Supply Chain Intelligence and FR Y-14Q datasets to obtain the sample of U.S. importers for our analysis. Then, we discuss a key limitation of the Panjiva data, specifically the redaction of some firm names/identifiers in the original bill of lading data.

Matching firms across the Panjiva and Y14 datasets. Panjiva and Y14 do not share common identifiers. Therefore, we apply a string match procedure on the firm names (and further selection on location) to link the firms across the two datasets. In Panjiva the firms have a unique Panjiva ID and in Y14 they are identified by a unique TIN (Taxpayer Identification Number assigned by the U.S. Internal Revenue Service). We proceed as follows.

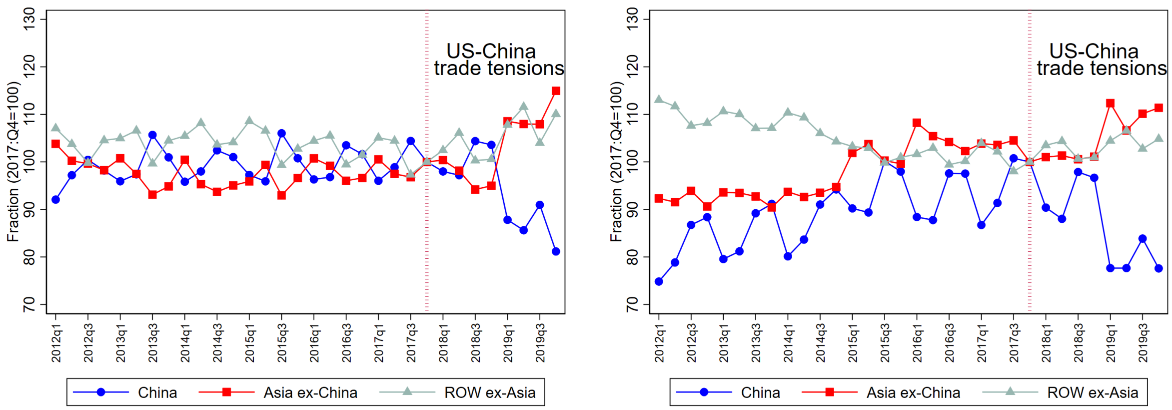
First, we clean and uniformize the firm names in the two datasets. Second, we conduct an exact match on firm name. For the firms that remain unmatched in this step, we bring additional information about the names of their ultimate corporate parent. For this purpose, we identify the corporate parent of U.S. importers using the crosswalks from S&P BECRS (Cross Reference Services Business Entity Linking) dataset which links firms between the Panjiva ID and the Capital IQ identifier (CIQ) in BECRS. The ultimate parent name and country come from Capital IQ Pro. Third, we clean and uniformize the parent names and match again (exactly) on firm name. In the few instances when we find several possible matches, we examine those records by hand and select the most probable match based on the firm's location (zipcode).

Over the sample period 2016–2019, Y14 dataset contains 97,200 total borrowers and the Panjiva dataset contains shipments to nearly 770,000 importers. This matching procedure yields a total number of 26,188 importing firms and 11,431 exporting firms. We are thus able to identify the importers that also have exporting activities and whose export products are subject to retaliatory tariffs (a baseline control variable). In Appendix A-III we describe the basic characteristics of U.S. importers using balance sheet data from Y14.

Name redactions in Panjiva. Panjiva contains information on maritime shipments only. Despite that, aggregated Panjiva data track the U.S. Census data closely during our sample period, as seen by comparing panel (a) in Figure A1 with panel (a) in Figure 1. That said, an important and well-known limitation of the Panjiva data is the redaction of some firms names. Firms can file a request with the U.S. CBP to redact their identity in the bill of lading. Redaction requests must be renewed every two years and firms with multiple names must file separate redaction requests for each name. Thus, we may observe the shipments of a given firm when it fails to redact all of its names, or when it fails to renew redaction requests

Figure A1: **Reallocation of imports from China, U.S. Census**

Panel A of the figure depicts the quarterly share of U.S. maritime imports by origin (China, Asia excluding China, and rest of the world excluding Asia). Maritime imports are measured in Customs Containerized Vessel Value. panel B depicts the quarterly share of total U.S. imports by origin (China, Asia excluding China, and rest of the world excluding Asia). Total imports are measured in Customs Value and cover all modes of transportation (maritime, airborne, and land (road/railroad)). Import shares are normalized to 100 in 2017:Q4. Source: Authors' calculations using U.S. Census.



(a) Maritime imports (b) Total imports

on time. Shipments with redacted firm names are dropped from the analysis because they lack firm names (consignee name) and identifiers (consignee Panjiva ID), so it is not possible to match redacted firms' names to the Y14 or follow their trade activities in Panjiva.

During the sample period 2016–2019, between 12.4% and 15.5% of shipment records are redacted, representing between 7% and 13% of import volume measured in TEU in any given year. Flaaen *et al.* (2023), who study the redaction problem in Panjiva in detail, report similar figures—between 10.6% and 14.2% of Panjiva identifiers are missing for U.S. importers during this period.

Across geographic regions, most of the redactions are for imports from countries in Asia and Pacific region (78%), followed by Europe (13.7%) and the Western Hemisphere (6.8%). This geographical distribution is similar to that of non-redacted shipments (for which the corresponding shares are 69.8%, 19% and 11%). The region that is most likely to have redacted import shipments is the Middle East & Central Asia (22%), followed by Asia and the Pacific (16%). Imports from other regions are redacted in proportions of less than 10%.

Worldwide, the products with the highest shares of redactions during 2016–2019 have the following 2-digit HS codes: 14 (Vegetable plaiting materials), 97 (Works of art; collectors' pieces and antiques), 96 (Miscellaneous manufactured articles), 82 (Tools, implements, cutlery, spoons and forks, of base metal), 55 (Man-made staple fibres); and 63 (Textiles, made up articles; sets; worn clothing and worn textile articles; rags).

Turning to China, the share of redacted shipments originating from China ranges between 15.6% to 18.8% during 2016–2019. Furthermore, these shipments represent up to 20% of the import volume in any given year. The product code with the highest shares of redacted shipments (36.6%) is 01 (Live animals), but there are only 41 such shipments during 2016–2019. Product codes with redacted shipments in proportions of between 25% and 30% include 55 (Man-made staple fibres), 30 (Pharmaceutical products), 53 (Other vegetable textile fibres; paper yarn and woven fabrics of paper yarn), 80 (Tin and articles thereof), 32 (Tanning or dyeing extracts; tannins and their derivatives; dyes, pigments and other colouring matter; paints and varnishes; putty and other mastics; inks), 31 (Fertilisers), 07 (Edible vegetables and certain roots and tubers), and 82 (Tools, implements, cutlery, spoons and forks, of base metal). Rare-earth metals have a redaction rate of 21.6% (28—Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes) and semi-conductors have a redaction rate of 14.6% (category 85—Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles). In the latter category, the semi-conductors that are most likely to be redacted are high-voltage electric conductors and fiber optic cables (6-digit HS code 854460—Insulated electric conductors; for a voltage exceeding 1000 volts) and 854470—Insulated electric conductors; optical fibre cables).

Given the redaction problem in Panjiva, some caution is warranted when interpreting our results. First, some of the time variation in import growth can be explained by the changing composition and size of the pool of redacted firms. Unfortunately, no additional information is available to enable a deeper analysis of these firms. Second, to the extent that the larger firms (e.g., multinationals) are more likely to redact their names, we would be missing their trade activities from the analysis. Whereas missing these large firms would be a concern given their likely disproportionate contribution to total trade (Gaubert and Itskhoki, 2021), the same firms are less likely to be dependent on bank financing—the focus of our analysis.

A-III U.S. Importer Characteristics

Our analysis focuses on the U.S. firms in FR Y-14Q dataset (that is, firms with outstanding loans from Y14-reporting banks) which can be matched to import and export records in the S&P Panjiva Supply Chain Intelligence dataset.

During 2016–2019, importers account for 29% of firms and exporters account for 12% of firms. For comparison, Antràs *et al.* (2024) document that the share of domestic importers was 24% and that of domestic exporters was 27% in the universe of firms with U.S. establishments in 2007 based on merged BEA-Census data. Furthermore, one in ten firms in the Y14 dataset is both an importer and an exporter. Importing activities are significantly more prevalent among publicly-listed firms.

Importers account for a significant share of economic activity of firms in the Y14 dataset. During 2016–2019, importing firms account for 41% of total assets, 37% of total debt, and 21% of total sales across all firms in the Y14 dataset. As shown in Figure A2, U.S. importers (in particular tariff-hit importers) are concentrated in the manufacturing, wholesale, and retail trade industries.

Table A1 below reports basic comparative descriptive statistics for importers versus other firms in the Y14 matched sample. Importers tend to be larger, have less cash and less leverage than other firms. Patterns are the same if we condition on firm 3-digit NAICS industry and state (not reported).

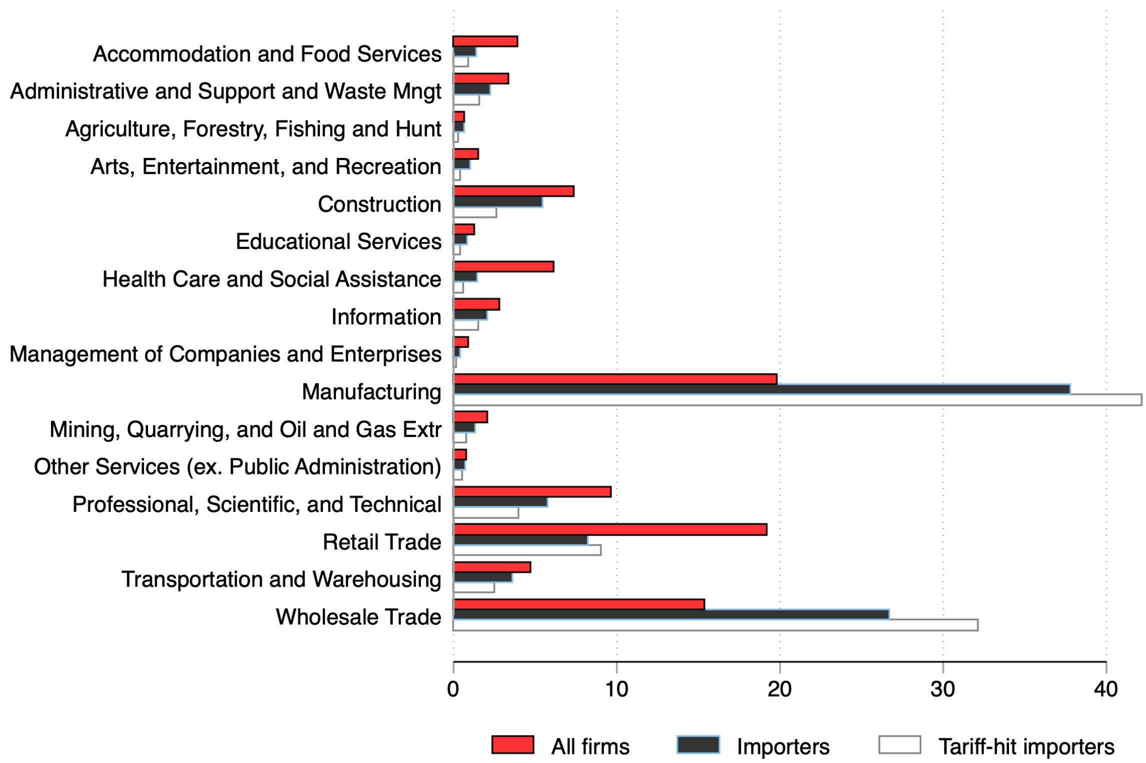
Table A1: **Importer characteristics**

This table reports average characteristics for all firms and by importer status in firm-year level data during 2016–2019.

	(1) **All Firms**	(2) **Importers**	(3) **Non-Importers**
Total assets (log)	17.13	17.49	16.96
Cash ratio (cash/assets)	13%	11%	14%
Leverage (debt/assets)	33%	28%	35%
ROA	16%	15%	16%
0/1 Firm with retaliatory tariffs	1%	2%	0%
0/1 Firm is multinational	2%	8%	0%
0/1 Firm is exporter	12%	33%	3%
0/1 Firm is public	3%	5%	2%

Figure A2: **Industry distribution of U.S. importers, 2016–2019**

This figure plots the industry shares of three groups of firms: (i) all firms in the Y14 data (importers, exporters, and other firms); (ii) importers identified using the Y14-Panjiva match, and (iii) tariff-hit importers. Source: Authors' calculations using S&P Panjiva Supply Chain Intelligence and FR Y-14Q.



A-IV Additional Results

Table A2: **Additional descriptive statistics**

This table shows descriptive statistics for variables used in the additional results and robustness checks. Sample periods refer to 2016–2019 period except in the placebo tests (Table A13). Sources: Authors' calculations using data from S&P Panjiva Supply Chain Intelligence, FR Y-14Q, and FR Y-9C.

Variable	(1) **Obs.**	(2) **Mean**	(3) **St. Dev.**	(4) **P25**	(5) **Median**	(6) **P75**
(A) Loan-level data						
Maturity (years)	1283554	6.457	4.633	3.995	5.005	7.570
Probability of default	1170318	0.025	0.087	0.003	0.007	0.018
0/1 Loan is non-performing	1283554	0.007	0.081	0.000	0.000	0.000
0/1 Loan is charged-off	1283554	0.003	0.051	0.000	0.000	0.000
Relationship intensity (loan share)	840197	0.058	0.160	0.005	0.022	0.077
(B) Bank-quarter data						
Total assets (log)	518	19.283	1.047	18.656	18.903	19.741
Capital ratio (CET1)	518	0.144	0.050	0.116	0.133	0.153
Core deposits (over liabilities)	518	0.597	0.207	0.521	0.679	0.754
Leverage (equity/assets)	518	0.118	0.025	0.103	0.116	0.132
Efficiency (overhead/assets)	497	0.030	0.010	0.025	0.027	0.032
Loan loss provisioning (over gross loans)	518	0.441	0.670	0.086	0.291	0.475
Loan loss reserves (over gross loans)	518	0.011	0.008	0.007	0.010	0.013
Nonpeforming loans (over gross loans)	518	0.012	0.009	0.007	0.010	0.014
Net chargeoffs (over gross loans)	518	0.007	0.011	0.002	0.004	0.006
Return on assets	518	0.019	0.013	0.012	0.016	0.022
Return on equity	518	0.171	0.114	0.100	0.139	0.206
0/1 Bank is specialized - Asia	518	0.116	0.320	0.000	0.000	0.000
(C) Firm-year data						
Accounts payable (over revenue)	29419	0.075	0.070	0.033	0.058	0.094

Table A3: **Balancing table: Tariff-hit vs. other firms**

This table reports average characteristics, lending and trade outcomes of tariff-hit importers (Column 1) and other firms (Column 2) in 2017 (conditional on 3-digit NAICS industry). Normalized differences between each pair of averages (the difference between the quartile average and the average of the other three quartiles, normalized by the square root of the sum of the corresponding variances) are reported in Column 3. Imbens and Wooldridge (2009) propose that two variables have "similar" means when the absolute normalized difference is less than 0.25.

	(1) **Tariff-hit importer**	(2) **Other firm**	(3) **Normalized Difference (1)-(2)**
Panel A. Firm characteristics:			
Total assets (log)	17.028	17.072	0.082
Liquidity (cash/assets)	0.105	0.135	0.058
Leverage (debt/assets)	0.281	0.342	0.072
Return on assets	0.152	0.158	0.020
0/1 Firm with retaliatory tariffs	0.030	0.002	-0.186
0/1 Firm is public	0.030	0.024	0.014
No. firms	N=5,658	N=72,765	
Panel B. Lending outcomes:			
Credit line utilization	0.354	0.353	-0.025
Interest rate (all loans)	0.036	0.035	-0.060
Interest rate (new loans)	0.038	0.037	-0.040
No. loans	N=29,632	N=362,939	

Table A4: **Balancing table: Specialized and other banks**

This table reports average characteristics of specialized banks (Column 1) and other banks (Column 2) in 2017. Specialized bank is a bank that offer cross-border trade financing services to firms in Asia (excluding China). P-values for a t-test of differences between each pair of averages (unadjusted for sample size) are reported in Column 3.

	(1) **Specialized bank**	(2) **Other bank**	(3) **p-value t-test (1)=(2)**
Total assets (log)	20.245	19.163	0.045
Capital ratio (CET1)	0.125	0.147	0.288
Core deposits (over liabilities)	0.705	0.579	0.278
Leverage (equity/assets)	0.110	0.119	0.502
Efficiency (overhead/assets)	0.027	0.031	0.471
Loan loss reserves (over gross loans)	0.013	0.011	0.720
Nonpeforming loans (over gross loans)	0.014	0.012	0.654
Net charge-offs (over gross loans)	0.005	0.007	0.764
Return on assets	0.018	0.022	0.570
Return on equity	0.167	0.200	0.607

Table A5: **Balancing table: Tariff-hit firms with specialized and other banks**

This table reports average characteristics, lending and trade outcomes for tariff-hit importers in a relationship with specialized banks (Column 1) and tariff-hit importers in a relationship with non-specialized banks (Column 2) in 2017 (conditional on 3-digit NAICS industry). Specialized bank is a bank that offer cross-border trade financing services to firms in Asia (excluding China). Normalized differences between each pair of averages (the difference between the quartile average and the average of the other three quartiles, normalized by the square root of the sum of the corresponding variances) are reported in Column 3. Imbens and Wooldridge (2009) propose that two variables have "similar" means when the absolute normalized difference is less than 0.25.

	(1)	(2)	(3)
	Tariff-hit importer		
	with specialized bank	**with other bank**	**Normalized Difference (1)-(2)**
Panel A. Firm characteristics:			
Total assets (log)	17.354	16.937	-0.202
Cash ratio (cash/assets)	0.107	0.105	-0.003
Leverage (debt/assets)	0.299	0.275	-0.079
ROA	0.152	0.151	0.004
0/1 Firm with retaliatory tariffs	0.031	0.030	-0.005
0/1 Firm is public	0.071	0.019	-0.245
No. firms	N=1,230	N=4,428	
Panel B. Lending outcomes:			
Credit line utilization	0.323	0.370	0.118
Interest rate (all loans)	0.035	0.037	0.109
Interest rate (new loans)	0.036	0.039	0.156
No. loans	N=10,556	N=19,076	

Table A6: **Balancing table: Unconstrained tariff-hit firms with specialized and other banks**

This table reports average characteristics, lending and trade outcomes for unconstrained tariff-hit importers in a relationship with specialized banks (top panel) and unconstrained tariff-hit importers in a relationship with non-specialized banks (bottom panel) in 2017 (conditional on 3-digit NAICS industry). In the top panel, unconstrained firms are defined as large firms with total assets above the median value. In the bottom panel, unconstrained firms are defined as investment grade firms, whose credit rating is BBB or above. Specialized bank is a bank that offer cross-border trade financing services to firms in Asia (excluding China). Normalized differences between each pair of averages (the difference between the quartile average and the average of the other three quartiles, normalized by the square root of the sum of the corresponding variances) are reported in Column 3. Imbens and Wooldridge (2009) propose that two variables have "similar" means when the absolute normalized difference is less than 0.25.

	(1)	(2)	(3)
	Tariff-hit importer		
	with specialized bank	**with other bank**	**Normalized Difference (1)-(2)**
	Unconstrained firms: Large (assets > median)		
Panel A. Firm characteristics:			
Total assets (log)	18.626	18.210	-0.213
Cash ratio (cash/assets)	0.100	0.096	-0.021
Leverage (debt/assets)	0.297	0.291	-0.007
ROA	0.143	0.129	-0.084
0/1 Firm with retaliatory tariffs	0.039	0.044	0.027
0/1 Firm is public	0.128	0.037	-0.331
No. firms	N=665	N=2101	
Panel B. Lending outcomes:			
Credit line utilization	0.268	0.345	0.225
Interest rate (all loans)	0.032	0.034	0.104
Interest rate (new loans)	0.035	0.037	0.122
No. loans	N=363	N=789	
	Unconstrained firms: Investment Grade (rating > BBB)		
Panel C. Firm characteristics:			
Total assets (log)	17.685	17.321	-0.157
Cash ratio (cash/assets)	0.131	0.152	0.154
Leverage (debt/assets)	0.228	0.175	-0.226
ROA	0.201	0.193	-0.033
0/1 Firm with retaliatory tariffs	0.032	0.035	0.021
0/1 Firm is public	0.100	0.026	-0.302
No. firms	N=600	N=1275	
Panel D. Lending outcomes:			
Credit line utilization	0.191	0.194	0.061
Interest rate (all loans)	0.027	0.026	-0.116
Interest rate (new loans)	0.030	0.028	-0.194
No. loans	N=250	N=428	

Table A7: **Additional lending outcomes**

This table reports OLS estimates from a regression of loan maturity (in years), ex-ante probability of default, and ex-post loan performance (dummmy variables for non-performing and charged-off loans) on the tariff-hit dummy variable interacted with the Post dummy. The data are at the loan level during 2016–2019. Sample specifications are the same as in Table 6. Probability of default is assessed internally by banks based on Basel II guidelines. Standard errors are double clustered by firm-quarter and bank. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Loan maturity**	**Probability of default**	**0/1 Loan is non-performing**	**0/1 Loan is charged-off**
Tariff-hit × Post × Specialized Bank [1]	0.0481***	0.0013	-0.0011	-0.0004
	(0.0139)	(0.0018)	(0.0009)	(0.0005)
Tariff-hit × Post × Other Bank [2]	0.0343	0.0044***	0.0004	-0.0000
	(0.0219)	(0.0015)	(0.0011)	(0.0003)
Observations	1,283,554	1,169,456	1,283,554	1,283,554
R-squared	0.7046	0.6600	0.3865	0.5380
Firm controls × Post	Y	Y	Y	Y
State × Industry × Quarter FE	Y	Y	Y	Y
Bank × Quarter FE	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y

Table A8: **Loan performance in bank-level data**

This table reports OLS estimates from a regression of loan loss provisioning (% gross loans), non-performing loans (% gross loans), and net charge-offs (% gross loans) on the specialized bank dummy. The data are at the bank-quarter level during 2016–2019 and are sourced from the FR Y-9C form. All specifications include bank controls (size, capital ratio, and core deposit share in total liabilities) as well as quarter and bank fixed effects. Standard errors are double clustered at the bank and quarter level. *** 1%, **5%, *10%.

	(1)	(2)	(3)
Dependent variables:	**Loan loss provisioning**	**Non-performing loan ratio**	**Net charge-off ratio**
Specialized bank × Post	-0.0004	-0.0022*	-0.0005
	(0.0005)	(0.0012)	(0.0003)
Observations	518	518	518
R-squared	0.9108	0.9452	0.9626
Bank controls	Y	Y	Y
Quarter FE	Y	Y	Y
Bank FE	Y	Y	Y

Table A9: **Role of trade credit**

This table reports OLS estimates from a regression of accounts payable as a share of total sales revenue from firms' balance sheets (a proxy for changes in direct trade credit received by importers from their suppliers) on the tariff-hit dummy interacted with the Post dummy. The data are at the firm-year level over 2016–2019. Firm controls include firm size (log-assets), leverage (debt/assets), cash ratio (cash/assets), profitability (ROA), all at the end of 2017, and a dummy the firm exporting products subject to retaliatory tariffs. Industry refers to 3-digit NAICS classification. Standard errors are clustered at the firm level. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Accounts Payable (% revenues)**			
Tariff-hit	-0.0004	0.0001		
	(0.0015)	(0.0014)		
Tariff-hit × Post	0.0004	0.0003	-0.0008	-0.0007
	(0.0014)	(0.0014)	(0.0012)	(0.0012)
Observations	29,371	29,018	28,190	27,863
R-squared	0.0579	0.0915	0.8245	0.8221
Firm controls	-	Y	-	Y
Firm controls × Post	-	-	-	Y
Firm FE	-	-	Y	Y
State × Year FE	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y

Table A10: **Information channel: Bank borrowing terms for unconstrained firms**

This table reports OLS estimates from a regression of lending terms on the tariff-hit dummy interacted with the Post dummy, with main DiD coefficient estimated by type of banking relationships for unconstrained firms. In columns 1-2, unconstrained firms are defined as large firms with total assets above the median value. In columns 3-4, unconstrained firms are defined as investment grade (IG) firms, whose credit rating is BBB or above. The data are at the loan level during 2016–2019. Sample specifications are the same as in Table 6. Standard errors are clustered by firm-quarter. *** 1%, **5%, *10%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **Credit line utilization**	(4) **Loan interest rate**
	Large Firms (assets > median)		**IG Firms** (rating > BBB)	
Tariff-hit×Post×0/1 Firm with specialized bank	0.0060	-0.0075	0.0091	-0.0195
	(0.0056)	(0.0238)	(0.0080)	(0.0502)
Tariff-hit×Post	0.0095**	0.0301	-0.0060	-0.0593
	(0.0043)	(0.0204)	(0.0064)	(0.0414)
Observations	379,890	441,577	116,954	111,628
R-squared	0.7338	0.7864	0.7741	0.8152
Firm controls × Post	Y	Y	Y	Y
State x Industry x Quarter FE	Y	Y	Y	Y
Bank x Quarter FE	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	-

A-V Robustness Checks

In this section, we present several robustness checks for our main results. Specifically, we discuss (a) the results obtained using a nearest-neighbor matching estimator; (b) tests for parallel trends; (c) the inclusion of a measure of the intensity of relationship banking; (d) results from the staggered treatment variable; (e) an alternative definition of bank specialization that requires banks to have local offices in Asia; (f) the robustness of the baseline results to the exclusion of wholesale and retail sectors, and publicly listed firms; and (g) the supply chain realignment results for all importers in the Panjiva data.

Matching Estimator. As discussed in Section 2, potential systematic differences between tariff-hit firms and other firms (or between specialized and other banks and the firms borrowing from these banks) could lead to a selection bias in our baseline results. Tables A3, A4, and Table A5 of balancing characteristics shows that the two groups of firms and banks, respectively, are similar along a broad set of observable characteristics. Nevertheless we check if our results are robust to an alternative estimator.

We proceed in two steps. First, we use the nearest-neighbor matching estimator (Abadie and Imbens, 2011) to construct control groups (of "nearest neighbors") for tariff-hit firms and for tariff-hit firms with specialized banks, respectively. Second, we re-run the DiD baseline regressions comparing tariff-hit firms with firms from these new control groups. The control groups are obtained by matching the firms exactly on the dummy for exporting products that are subject to retaliatory tariffs, state, and industry in bank credit regressions (Columns 1-2) and additionally on HS6 product in the trade regressions (Columns 3-5). Furthermore, across specifications we match the nearest-neighbors on all time-varying firm characteristics (size, leverage, liquidity, and ROA).

Panel A of Table A11 shows coefficients that are virtually identical to those in Columns 1-2 in Table 5 and Panel B of Table 3. In fact, the magnitudes of the estimates for bank credit outcomes are larger than in the baseline analysis, showing a 0.9 pps increase in credit line utilization and 7.8 bps increase in loan rates among tariff-hit firms after the tariffs (compared to 0.7 pps and 3.6 bps in Table 5). Panel B of Table A11 reports matching estimates comparable to Columns 1-2 of Table 6 and Columns 1-3 of Table 9. Estimates are statistically significant, have the expected signs, and are similar in magnitude to the original DiD specifications. Differences in credit outcomes between specialized and other banks are even starker when we use the matched samples of firms. In particular, we now find larger credit line drawdowns by firms borrowing from specialized banks (by 1.1 pps, Column 1) and larger interest rates offered by other banks (9.4 bps in Column 2) compared to our baseline estimates.

Parallel Trends in Trade Outcomes. Figure 1 suggests the presence of pre-trends in trade reallocation within Asia (owing, in part, to the gradual shift of U.S. imports to lower labor cost markets). To mitigate potential biases caused by pre-trends, we follow Autor *et al.* (2024) and augment Equation 1 with an additional control variable ("pre-trend control"), defined as the firm-specific change in the outcome variable over the pre-period (2016–2017). Table A12 shows that the pre-trend variable is precisely estimated in all cases, but the DiD coefficient of interest "Tariff-hit $\times$ Post" remains statistically significant at 1% level and is somewhat smaller. Focusing on Columns 4-5 and comparing the new results with the baseline Table 3, the probability of entry into a relationship with a new Asian supplier (ex-China) declines from 90.3% to 70.7%, whereas the number of new Asian suppliers declines from 75.4% to 57.4%.

Parallel Trends in Bank Credit Outcomes. Identification of the DiD coefficient of interest δ_1 in Equation 3 hinges on the assumption that tariff-hit and other firms are on "parallel trends" with respect to lending outcomes before the tariffs. We test this assumption with a placebo test that moves the period of analysis back by two or three years (Table A13). In Columns 1–2, we compare lending outcomes during 2013–2014 (pre) versus 2015–2016 (post); and in Columns 3–4, between 2014–2016 (pre) versus 2016–2017 (post). The estimates shown in Panel A of Table A13 show no association between firms' tariff exposure in 2018–2019 and lending outcomes a few years before the imposition of tariffs. The DiD estimates are not statistically significant in most specifications (in Column 3 the negative coefficient indicates lower credit line utilizations and hence lower credit demand). The results for bank credit outcomes by specialized versus other banks (Table A13, Panel B) also reveal no patterns that would suggest a confounding effect. These placebo tests mitigate concerns that pre-existing trends might influence our main findings.

In addition, for our baseline results (corresponding to the specifications in Columns 1 and 3 from Table 5), we break down the main DiD coefficient estimates on "Tariff-hit$\times$Post" by quarter. The visual inspection of the quarterly dynamic DiD coefficients—plotted in Figure A3—suggests an absence of pre-trends in credit outcomes.

Alternative Control Group in Bank Credit Regressions. In the main bank credit regressions (Table 5), the control group comprises importers that are not subject to tariffs and all other firms (regardless of their importer status). Table A14 shows that our results are robust to restricting the sample to importing firms such that the control group comprises the importers not subject to the 2018–2019 tariffs (as in the trade regressions). Given that retaining only loans to importers implies losing more than 60% of loans from the Y14 data, regression coefficients are qualitatively similar to the baseline analysis, but are less precisely estimated.

Relationship Banking. In Table A15 we check if our main bank credit results are sensitive to controlling for relationship banking. Following the literature (Elsas, 2005; Kysucky and Norden, 2016), our proxy of relationship banking intensity is the end-2017 bank-firm loan share. The results show that the DiD coefficient estimates for "Tariff-hit×Post" are virtually unchanged when the specification includes the "Relationship banking" term in interaction with "Post" and "Tariff-hit×Post." Estimates in columns 2 and 4 indicate that banks with a higher ex-ante loan exposure to firms charge higher interest rates on loans (by close to 20 bps), which aligns with the intuition that borrowers demand more credit from their relationship lenders. However, this effect does not differ across tariff-hit versus other firms.

Staggered Treatment. After the initial round of tariffs in January 2018 on washing machines and solar panels (affecting all trading partners), subsequent tariff increases targeting Chinese imports were implemented in four waves: (i) 25% tariffs applied on $34 billion worth of products in July 2018; (ii) 25% tariffs applied on $16 billion worth of products in August 2018; (iii) 10% tariff applied on $200 billion worth of products in September 2018, further raised to 25% in May 2019; and (iv) 15% tariff applied on $112 billion worth of products in September 2019. Here, we test the robustness of our main results to the use of a staggered treatment defined such that the firms with imported products hit by tariffs in 2018 get value one in both years 2018–2019, while those with imported products hit by tariffs in 2019 get value zero in 2018 and one in 2019. More than 80% of firms are "treated" in 2018 when the lion's share of tariffs goes into effect.

The results with "staggered treatment" are reported in Table A16. Panel A refers to main effects for tariff-hit firms on access to credit and supply chain realignment reported in Columns 1-2 in Table 5 and Panel B of Table 3. The coefficients across all specifications have the expected signs and are statistically significant as in the baseline analysis. Furthermore, allowing for staggered treatment in estimating differential effects by bank type (panel B) produces very similar findings to those on bank credit reported in Columns 1-2 of Table 6 and supply chain realignment in Columns 1-3 of Table 9.

Alternative Definition of Bank Specialization. The banks identified as "specialized" in the baseline analysis offer cross-border trade finance services to corporate clients in Asia (ex-China). This requirement is a strong predictor of a bank's local presence in Asian countries. In fact, all specialized banks in the baseline analysis have some degree of local presence in Asia through branches and/or foreign subsidiaries. We check that our results are robust to expanding the sample with several banks that have local presence in Asia but do not necessarily offer cross-border trade finance services. Our proxy for local presence is that the bank should have positive local claims (that is, it makes loans in foreign or domestic currency to local residents) in 2016–2017, sourced from the FFIEC 009 form. *Results for alternative definition of bank specialization are pending clearance and not shown in the current draft.*

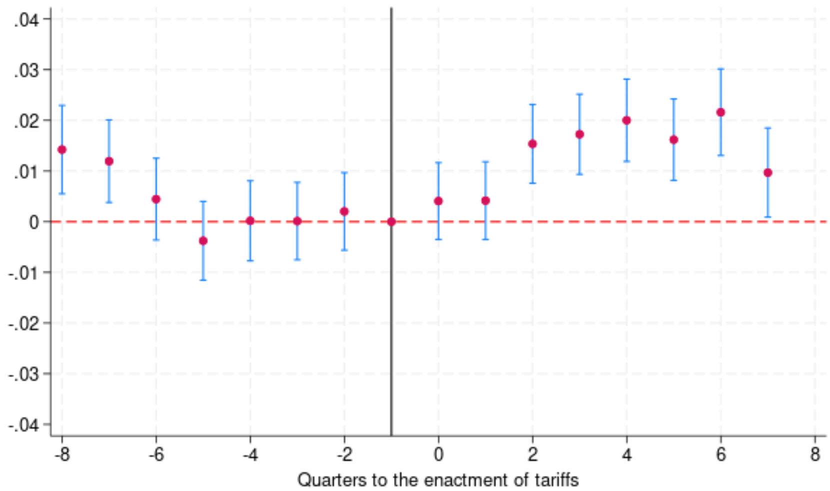
Publicly-listed Firms. In Table A17, we report the estimation results of specifications similar to Table 3 but estimated in the sample of private firms. Dropping public firms results in a slight reduction in sample sizes. However, all results remain similar (if anything, some strengthen) relative to the baseline results, both in terms of economic magnitudes and significance. For instance, the loan interest rate effect of tariffs is 5.1 bps for private firms (Column 2 of Table A17) compared to 3.6 bps in the full sample (Column 2 of Table 3).

Wholesale and Retail Sectors. Wholesale and retail firms hit by tariffs differ from firms in other sectors (primarily manufacturing, see Figure A2) as they do not engage in production of goods and services. Therefore, these firms are less likely to receive loans for capital investment or research and development. Firms in wholesale and retail sectors are also more likely to seek out suppliers of final goods rather than intermediate goods, which could affect the overall cost of finding alternative suppliers. Table A18 replicates our main results in a sample that excludes firms in wholesale and retail sectors. The estimates paint a similar picture as in the baseline Tables 3 and 5. Notably, we see somewhat stronger evidence of supply chain realignment compared to the full sample (Columns 3-5).

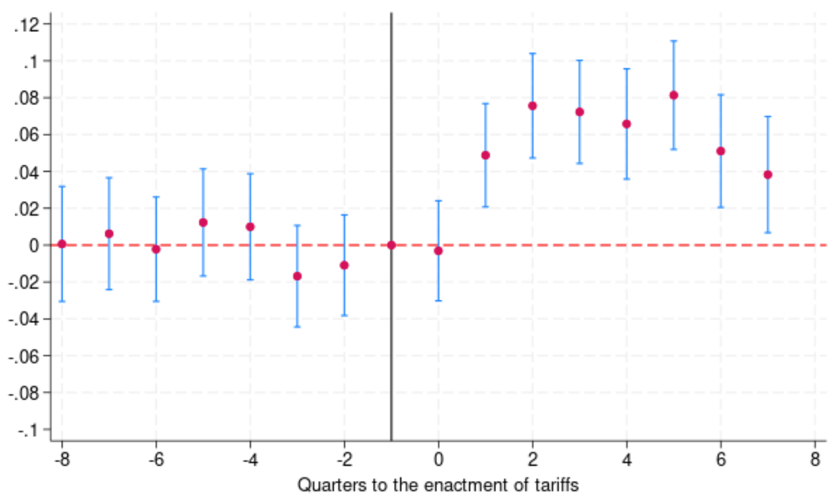
All Firms in Panjiva. In Table A19, we report the estimation results of specifications similar to Table 3 but estimated using the universe of firms in Panjiva. This sample is almost an order of magnitude larger than the one used in the main analysis, as it includes firms that are not matched to the Y14 data and for which we do not have industry classification and balance sheet data. Even without the full set of controls from the baseline analysis, the results closely mirror those of matched sample. However, the coefficient magnitudes of the DiD term Tariff-hit×Post are smaller than those in Table 3. Despite the specification differences, the signs of all estimated coefficients are the same as in the baseline results.

Figure A3: **Dynamic DiD coefficients for bank credit outcomes**

This figure shows the effects of firm exposure to the 2018–2019 tariffs on credit line utilizations and loan interest rates. Each chart plots the estimated DiD coefficients and the associated 90% confidence levels of the dynamic variant of the specifications in Columns 1 and 2 in Table 5 with interaction effects between "Tariff-hit" dummy and quarterly dummies (with base period 2017:Q4). Tariff-hit dummy takes value one for firms that imported at least one product subject to China tariffs during 2018 or 2019. Source: Authors' calculations using data from S&P Panjiva Supply Chain Intelligence and FR Y-14Q.



(a) Credit line utilization rate



(b) Loan interest rates

Table A11: **Supply chain reallocation and bank borrowing: Matching estimator**

This table reports OLS estimates from regressions of bank credit outcomes (Bank credit, Columns 1-2) and PPML estimates from regressions of trade outcomes (Realignment to Asia (ex-China), Columns 3-5) on the tariff-hit dummy variable interacted with the Post dummy (Panel A), and on the "Tariff-hit × Post" term estimated separately for loans from specialized banks versus other banks using a spline term (there is no omitted category) (Panel B). "Specialized bank" is a dummy for banks with positive cross-border trade claims on nonfinancial firms in Asia (ex-China). The control group is obtained using a matching approach. We employ the nearest-neighbor matching estimator (Abadie and Imbens, 2011) to construct control groups, by (a) matching exactly on time-invariant firm characteristics (dummy for importer that exports products subject to retaliatory tariffs), state, and industry in Columns 1-2 and additionally on HS6 product Columns 3-5, and (b) matching in all cases on time-varying firm characteristics (size, leverage, liquidity, and ROA). In Panel A, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 5 (Columns 1-2) and 3 (Columns 4-6), respectively. In Panel B, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 6 (Columns 1-2) and 9 (Columns 1-3), respectively. Bank credit outcomes refer to all outstanding loans. *** 1%, **5%, *10%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan rate**	(3) **0/1 Entry into Asia**	(4) **# Asian suppliers gained**	(5) **Asian import share**
	Bank credit		**Realignment to Asia (ex-China)**		
			(A) Baseline		
Tariff-hit × Post	0.0095**	0.0782***	0.5904***	0.5223***	0.3690***
	(0.0045)	(0.0151)	(0.0964)	(0.1177)	(0.0699)
Observations	106,592	115,073	50,460	50,460	53,734
R-squared	0.7833	0.8433	-	-	-
			(B) By Bank Specialization		
Tariff-hit×Post×Specialized Bank [1]	0.0110**	0.0483	0.5899**	0.5402**	0.3422***
	(0.0043)	(0.0609)	(0.2306)	(0.2424)	(0.1156)
Tariff-hit×Post×Other Bank [2]	0.0085	0.0936***	0.5104**	0.4374**	0.3090***
	(0.0060)	(0.0211)	(0.2157)	(0.2089)	(0.1102)
Observations	106,592	115,073	41,149	41,149	44,053
R-squared	0.7833	0.8433	-	-	-
p-value t-test (1) > (2)	-	-	0.039	0.084	0.209
Matching variables:					
Time	Y	Y	-	-	-
Firm state	Y	Y	Y	Y	Y
Firm industry	Y	Y	Y	Y	Y
Product (HS6)	-	-	Y	Y	Y
Firm subject to retaliatory tariffs	Y	Y	Y	Y	Y
Firm size	Y	Y	Y	Y	Y
Firm leverage	Y	Y	Y	Y	Y
Firm ROA	Y	Y	Y	Y	Y
Firm cash	Y	Y	Y	Y	Y

Table A12: **Robustness of supply chain results to pre-trend correction**

This table reports PPML estimates from a regression of trade outcomes on the tariff-hit dummy variable interacted with the Post dummy. Sample specifications are the same as in Table 3, but they also apply the Autor *et al.* (2024) correction for potential pre-trends. This correction requires including an additional control variable ("pre-trend control") defined as the firm-specific change in the outcome variable over the pre-period (2016–2017). Semi-elasticities are calculated as $[\exp(\beta_1) - 1] \times 100$. Standard errors are double clustered at the firm and product level. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**0/1 Exit**	**# Chinese suppliers lost**	**Import share China**	**0/1 Entry**	**# Asian suppliers gained**	**Import share Asia**
	(A) Realignment from China			**(B) Realignment to Asia (ex-China)**		
Tariff-hit × Post	0.4526***	0.4233***	-1.3444***	0.5348***	0.4534***	0.3461***
	(0.1106)	(0.1287)	(0.1915)	(0.0373)	(0.0388)	(0.0202)
Pre-trend control	0.7041***	0.0768***	0.6620***	1.0543***	0.0997***	0.6946***
	(0.0094)	(0.0108)	(0.0066)	(0.0244)	(0.0220)	(0.0069)
Semi-elasticity (%)	57.2	52.7	-73.9	70.7	57.4	41.3
Observations	151,437	151,437	159,073	122,543	122,543	126,803
Firm controls × Post	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	Y
Product × Year FE	Y	Y	Y	Y	Y	Y
Product × Firm FE	Y	Y	Y	Y	Y	Y

Table A13: **Placebo tests: Pre-trade tensions periods of analysis**

This table reports OLS estimates from Placebo tests of the specifications in Tables 5–6 that shift the window of analysis from the baseline 2016–2019 to 2013–2016 (columns 1-2) or 2014–2017 (columns 3-4). In Panel A, sample specifications are the same as in Table 5. In Panel B, sample specifications are the same as in Table 6. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Credit line utilization**	**Loan interest rate**	**Credit line utilization**	**Loan interest rate**
	2013–14 vs 2015–16		**2014–15 vs 2016–17**	
	(A) Baseline			
Tariff-hit × Post	0.0012	-0.0001	-0.0097***	0.0001
	(0.0024)	(0.0001)	(0.0021)	(0.0001)
Observations	659,784	771,615	749,042	878,769
R-squared	0.7479	0.7827	0.7498	0.7885
	(B) By Bank Specialization			
Tariff-hit×Post×Specialized Bank	-0.0038	-0.0000	-0.0113**	0.0004***
	(0.0044)	(0.0003)	(0.0046)	(0.0001)
Tariff-hit×Post×Other Bank	0.0046	-0.0002	-0.0086*	-0.0002
	(0.0047)	(0.0003)	(0.0047)	(0.0002)
Observations	659,784	771,615	749,042	878,769
R-squared	0.7479	0.7827	0.7498	0.7885
Firm controls × Post	Y	Y	Y	Y
State x Industry x Quarter FE	Y	Y	Y	Y
Bank x Quarter FE	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y

Table A14: **Bank credit: Robustness to importer-only control group**

This table reports OLS estimates from a regression of bank credit outcomes on the tariff-hit dummy variable interacted with the Post dummy. Sample specifications are the same as in Tables 5 and 6, respectively, except that the control group includes only importing firms. Bank credit outcomes are for all outstanding loans. *** 1%, **5%, *10%, #15%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **Credit line utilization**	(4) **Loan interest rate**
Tariff-hit × Post	0.0062***	0.0126#		
	(0.0024)	(0.0084)		
Tariff-hit × Post × Specialized bank [1]			0.0061	-0.0157
			(0.0039)	(0.0190)
Tariff-hit × Post × Other Bank [2]			0.0063#	0.0279*
			(0.0043)	(0.0157)
Observations	295,501	321,332	295,501	321,332
R-squared	0.7457	0.8032	0.7457	0.8032
p-value t-test Ha: |1| > |2|			0.489	0.057
Firm controls × Post	Y	Y	Y	Y
State × Industry × Quarter FE	Y	Y	Y	Y
Bank × Quarter FE	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y

Table A15: **Control for intensity of bank-firm lending relationship**

This table reports OLS estimates from a test of the specifications in Tables 5-6 that additionally controls for relationship intensity, measured as the end-2017 bank loan share to a given firm. Columns 1–6 present several variants of the main specifications in Tables 5-6 that sequentially add interactions of "Relationship intensity" with the Post dummy, and, respectively, with the tariff-hit dummy. Bank credit outcomes are for all outstanding loans. *** 1%, **5%, *10%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **Credit line utilization**	(4) **Loan interest rate**	(5) **Credit line utilization**	(6) **Loan interest rate**
Tariffs-hit × Post	0.0065***	0.0346***	0.0077***	0.0394***		
	(0.0021)	(0.0076)	(0.0023)	(0.0080)		
Tariffs-hit × Post × Specialized Bank [1]					0.0067*	0.0199
					(0.0033)	(0.0215)
Tariffs-hit × Post × Other Bank [2]					0.0085**	0.0532***
					(0.0039)	(0.0175)
Relationship intensity × Post	-0.0035	0.1950***	-0.0026	0.1992***	-0.0026	0.2004**
	(0.0066)	(0.0283)	(0.0067)	(0.0287)	(0.0131)	(0.0867)
Tariffs-hit × Relationship intensity × Post			-0.0235	-0.1005	-0.0263	-0.1487
			(0.0317)	(0.1125)	(0.0475)	(0.1477)
Observations	730,612	840,197	731,850	840,197	731,850	840,197
R-squared	0.7512	0.8048	0.7513	0.8048	0.7513	0.8048
p-value t-test Ha: $\lvert 1\rvert > \lvert 2\rvert$					0.2965	-
Firm controls × Post	Y	Y	Y	Y	Y	Y
State × Industry × Quarter FE	Y	Y	Y	Y	Y	Y
Bank × Quarter FE	Y	Y	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y	Y	Y

Table A16: **Supply chains realignment and bank credit: Staggered treatment**

This table reports OLS estimates from regressions of bank credit outcomes (Bank credit, Columns 1-2) and PPML estimates from regressions of trade outcomes (Realignment to Asia (ex-China), Columns 3-5) on the tariff-hit dummy variable interacted with the Post dummy (Panel A), and on the "Tariff-hit × Post" term estimated separately for loans from specialized banks versus other banks using a spline term (there is no omitted category) (Panel B). "Specialized bank" is a dummy for banks with positive cross-border trade claims on nonfinancial firms in Asia (ex-China). In Panel A, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 5 (Columns 1-2) and 3 (Columns 4-6), respectively. In Panel B, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 6 (Columns 1-2) and 9 (Columns 1-3), respectively. Differently from the main tables, the tariff-hit dummy is equal to one for firms that imported during 2016–2017 from a Chinese supplier products that were subject to tariffs in the precise year (2018 or 2019) when the tariffs were enacted. Bank credit outcomes refer to all outstanding loans. *** 1%, **5%, *10%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **0/1 Entry into Asia**	(4) **# Asian suppliers gained**	(5) **Asian import share**
	Bank credit		**Realignment to Asia (ex-China)**		
			(A) Baseline		
Tariff-hit×Post	0.0062***	0.0280***	0.6860***	0.6046***	0.3969***
	(0.0022)	(0.0077)	(0.0325)	(0.0383)	(0.0208)
Observations	775,974	890,517	122,543	122,543	126,803
R-squared	0.7586	0.8079	-	-	-
			(B) By Bank Specialization		
Tariff-hit×Post×Specialized Bank [1]	0.0047	0.0008	0.7138***	0.6488***	0.4129***
	(0.0028)	(0.0218)	(0.1536)	(0.1767)	(0.0760)
Tariff-hit×Post×Other Bank [2]	0.0071*	0.0427**	0.6528***	0.5586***	0.3960***
	(0.0037)	(0.0174)	(0.1478)	(0.1666)	(0.0859)
Observations	775,974	890,517	101,290	101,290	105,881
R-squared	0.7586	0.8079	-	-	-
p-value t-test Ha: |1| > |2|	0.239	0.085	0.040	0.042	0.285
Firm controls × Post	Y	Y	Y	Y	Y
State × Year	-	-	Y	Y	Y
Industry × Year	-	-	Y	Y	Y
Product × Firm	-	-	Y	Y	Y
Product × Year	-	-	Y	Y	Y
State × Industry × Quarter FE	Y	Y	-	-	-
Bank × Quarter FE	Y	Y	-	-	-
Bank × Firm FE	Y	Y	-	-	-

Table A17: **Drop publicly listed firms**

This table reports OLS estimates from regressions of bank credit outcomes (Bank credit, Columns 1-2) and PPML estimates from regressions of trade outcomes (Realignment to Asia (ex-China), Columns 3-5) on the tariff-hit dummy variable interacted with the Post dummy (Panel A), and on the "Tariff-hit × Post" term estimated separately for loans from specialized banks versus other banks using a spline term (there is no omitted category) (Panel B). The sample drops publicly-listed firms. "Specialized bank" is a dummy for banks with positive cross-border trade claims on nonfinancial firms in Asia (ex-China). In Panel A, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 5 (Columns 1-2) and 3 (Columns 4-6), respectively. In Panel B, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 6 (Columns 1-2) and 9 (Columns 1-3), respectively. *** 1%, **5%, *10%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **0/1 Entry into Asia**	(4) **# Asian suppliers gained**	(5) **Asian import share**
	Bank credit		**Realignment to Asia (ex-China)**		
			(A) Baseline		
Tariff-hit×Post	0.0072***	0.0512***	0.6384***	0.5577***	0.3861***
	(0.0022)	(0.0076)	(0.0321)	(0.0376)	(0.0214)
Observations	639,566	767,298	117,825	117,825	121,998
R-squared	0.7641	0.8162	-	-	-
			(B) By Bank Specialization		
Tariff-hit×Post×Specialized Bank [1]	0.0047*	0.0246	0.6805***	0.6151***	0.4149***
	(0.0025)	(0.0153)	(0.1714)	(0.1751)	(0.0999)
Tariff-hit×Post×Other Bank [2]	0.0088**	0.0663***	0.6079***	0.5183***	0.3774***
	(0.0040)	(0.0173)	(0.1535)	(0.1641)	(0.0942)
Observations	639,566	767,298	96,778	96,778	101,311
R-squared	0.7641	0.8162	-	-	-
p-value t-test Ha: |1| > |2|	0.158	0.046	0.060	0.085	0.137
Firm controls × Post	Y	Y	Y	Y	Y
State × Year	-	-	Y	Y	Y
Industry × Year	-	-	Y	Y	Y
Product × Firm	-	-	Y	Y	Y
Product × Year	-	-	Y	Y	Y
State × Industry × Quarter FE	Y	Y	-	-	-
Bank × Quarter FE	Y	Y	-	-	-
Bank × Firm FE	Y	Y	-	-	-

Table A18: **Drop firms in wholesale and retail trade sectors**

This table reports OLS estimates from regressions of bank credit outcomes (Bank credit, Columns 1-2) and PPML estimates from regressions of trade outcomes (Realignment to Asia (ex-China), Columns 3-5) on the tariff-hit dummy variable interacted with the Post dummy (Panel A), and on the "Tariff-hit × Post" term estimated separately for loans from specialized banks versus other banks using a spline term (there is no omitted category) (Panel B). The sample drops firms in the wholesale and retail trade sectors. "Specialized bank" is a dummy for banks with positive cross-border trade claims on nonfinancial firms in Asia (ex-China). In Panel A, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 5 (Columns 1-2) and 3 (Columns 4-6), respectively. In Panel B, the model specifications in Columns 1-2 and in Columns 3-5 are the same as in Tables 6 (Columns 1-2) and 9 (Columns 1-3), respectively. *** 1%, **5%, *10%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **0/1 Entry into Asia**	(4) **# Asian suppliers gained**	(5) **Asian import share**
	Bank credit		**Realignment to Asia (ex-China)**		
			(A) Baseline		
Tariff-hit×Post	0.0062***	0.0280***	0.7196***	0.6178***	0.4264***
	(0.0022)	(0.0077)	(0.0472)	(0.0558)	(0.0318)
Observations	775,974	890,517	48,206	48,206	52,841
R-squared	0.7586	0.8079	-	-	-
			(B) By Bank Specialization		
Tariff-hit×Post×Specialized Bank [1]	0.0047	0.0008	0.7574***	0.6938***	0.4667***
	(0.0028)	(0.0218)	(0.1996)	(0.2394)	(0.1196)
Tariff-hit×Post×Other Bank [2]	0.0071*	0.0427**	0.6950***	0.5640***	0.4344***
	(0.0037)	(0.0174)	(0.1555)	(0.1713)	(0.0909)
Observations	775,974	890,517	40,276	40,276	44,614
R-squared	0.7586	0.8079	0.7835	0.7836	0.7837
p-value t-test Ha: $\|1\| > \|2\|$	0.239	0.085	0.218	0.165	0.280
Firm controls × Post	Y	Y	Y	Y	Y
State × Year	-	-	Y	Y	Y
Industry × Year	-	-	Y	Y	Y
Product × Firm	-	-	Y	Y	Y
Product × Year	-	-	Y	Y	Y
State × Industry × Quarter FE	Y	Y	-	-	-
Bank × Quarter FE	Y	Y	-	-	-
Bank × Firm FE	Y	Y	-	-	-

Table A19: **Supply chain reallocation: All firms in Panjiva**

This table reports PPML estimates from a regression of trade outcomes on the tariff-hit dummy variable interacted with the Post dummy. Sample specifications are the same as in Table 3 but the sample includes all firms in the Panjiva dataset (not necessarily matched to the Y14), therefore firm controls (and industry × year fixed effects) are omitted. Standard errors are double clustered at the firm and product level. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables:	**0/1 Exit**	**# Chinese suppliers lost**	**Import share China**	**0/1 Entry**	**# Asian suppliers gained**	**Import share Asia**
	(A) Realignment from China			**(B) Realignment to Asia (ex-China)**		
Tariff-hit × Post	0.1969***	0.1438***	-0.0665***	0.3207***	0.2620***	0.0528***
	(0.0086)	(0.0100)	(0.0048)	(0.0062)	(0.0083)	(0.0035)
Observations	1,159,577	1,159,577	809,498	1,061,771	1,061,771	730,383
Firm FE	Y	Y	Y	Y	Y	Y
State × Year FE	Y	Y	Y	Y	Y	Y
Product × Firm FE	Y	Y	Y	Y	Y	Y
Product × Year FE	Y	Y	Y	Y	Y	Y