Bank Financing of Global Supply Chains*

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Finding new international suppliers is costly, so most importers source inputs from a single country. We match shipment data with the U.S. credit register to analyze the role of banks in mitigating trade search costs during the 2018-2019 U.S.–China trade tensions. 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 credit lines and taking out loans at higher rates. Banks offering trade finance services in Asia eased both financial and information frictions.

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1 Introduction

In recent years, rising trade tensions, geopolitical risks, and the pandemic have disrupted international trade flows and supply chains. In response, U.S. importers have started a "great reallocation" that is changing the geography of international trade (Fajgelbaum *et al.*, 2024). Finding new international trade partners involves significant search costs (Grossman *et al.*, 2024), so relationships along the supply chain tend to be sticky and even large 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. This paper asks whether and how commercial banks help importers mitigate search frictions and hence 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. It takes close to three years for the average importer to match to a new supplier in Asian countries outside China.

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 trade in foreign markets to help borrowers with information about potential supplier networks, reducing informational asymmetries about foreign markets. As a result, tariff-hit importers with specialized banks are 15 percentage points (pps) more likely to find new suppliers outside China and grow their Asian import shares by 5.6 pps more than tariff-hit importers with other banks. In addition, tariff-hit importers are faster by close to 6 months in establishing a new supplier relationship in a given country if they work with a specialized bank with local presence in that particular country. 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 leading supplier of goods to the U.S. (accounting for more than one-fifth of total U.S. imports) and most tariffs targeted products *imported from China*, whereas those affecting other trade partners were product-specific. 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. In this framework, supply chain realignment increases with tariffs and specialized lenders with privileged access to information about specific foreign markets can lower the cost of matching to new suppliers.

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 relationships that are matched to firm and bank balance sheets. These data have 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.[1]

In more detail, we use shipment-level data from S&P Panjiva Supply Chain Intelligence (Panjiva 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.[2] These data enable us to track bilateral relationships between U.S. importers and individual 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 reported by the largest banks since 2012. Matching the Panjiva and Y14 datasets (Section 2) allows us to present the first firm-level evidence on importers' use of bank credit in the reallocation of supply chains.

Our main results are 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 are noticeable a few quarters after the first wave of tariffs in early 2018. Difference-in-differences (DiD) regressions on firm-product-quarter 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 after the enactment of tariffs. As a result, the import share from China declines by 86%, whereas the import share from Asian

[1] 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.

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

markets (excluding China) increases by 47% for the average tariff-hit firm during 2018–2019.

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 3). Indeed, Cox proportional hazards regressions show that diversified U.S. importers who had suppliers in Asia before 2018—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 establishing new supplier relationships motivate us next to examine the role of specialized banks in facilitating this reallocation.

Third, we analyze bank credit flows (Section 4) and show that tariff-hit U.S. importers increase 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 pre-committed by the bank and can be tapped as long as the borrowers maintain creditworthiness and covenants are not breached (Sufi, 2009), therefore higher credit line utilizations suggest higher credit demand. In addition, tariff-hit firms obtain new loans at higher interest rates (by close to 18 bps), which also suggests increased credit demand.

Fourth, we turn to the role of banks in mitigating search frictions in trade (Section 5). Some banks should be better positioned for this purpose as they specialize 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 affords them informational advantages and the ability to offer better loan terms (a *credit* channel), as in Blickle *et al.* (2023). 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. Our analysis reveals that a relatively lower cost of credit for importers with specialized banks is associated with a higher likelihood of finding new suppliers outside China. These results reflect the value of relationships with banks specialized in trade finance to *Asian* markets and not necessarily a global business model, as relationships with banks specialized in *Europe* (not Asia) have no effect on credit or trade outcomes for firms searching for suppliers in Asia.

In addition to advantageous lending terms, specialized banks can reduce informational asymmetries about foreign markets by offering information about potential suppliers in those markets through advisory and consulting services (an *information* channel). Two pieces of evidence support this channel. First, firms with specialized banks are more likely to match to new Asian suppliers in those particular countries where a specialized bank also operates local offices such as branches/subsidiaries. This result supports the notion of "local bank network effects" and is robust to alternative measures of such networks such as previous syndicated lending activities to local borrowers and pre-existing ties with local correspondent banks. Second, bank-level income statements reveal that the Asian subsidiaries of specialized U.S. banks have 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 or deteriorating asset quality: 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 measure to Europe instead of Asia; (c) controlling for relationship banking; (d) allowing for staggered tariff treatment of U.S. importers capturing the enactment of tariffs in several waves; and (e) dropping public firms or multinational firms based on an alternative definition.

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; Antràs and Foley, 2015; Bronzini and D'Ignazio, 2017; Claessens and Van Horen, 2021; Berthou *et al.*, 2024; Matray *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.[3] Benguria and Saffie (2024) show that industry-level financial constraints hinder the reallocation of U.S. exports away from retaliating countries. Beyond bringing complementary evidence on the effect of bank financing on firms' trade activities, our paper uses granular information on bank activities to understand the mechanisms through which bank credit helps U.S. importers—most of which are private bank-dependent firms—diversify their input sourcing. In particular, 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

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

with information services. In addition, our analysis suggests that firm relationships with 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).[4] 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.

[4] 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. raised tariff rates 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%.[5] To study the effects of the 2018–2019 tariffs on supply chains and bank 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.

Below, we discuss each dataset in detail and the process of merging the data for the analysis. 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 on individual loan contracts to mostly private bank-dependent firms.

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

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

unit).[6]

One 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. firms' names and addresses, which enables us to match them to the borrowers in 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 firm 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 the U.S. Panjiva data only contains maritime shipments, 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 are predominantly imported from Mexico and Canada.[7]

Despite its 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).

[6] 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.

[7] Nevertheless, we explore the extent of export rerouting by Chinese firms via foreign affiliates, which could contribute "hidden exposures" of U.S. firms to Chinese suppliers (Baldwin *et al.*, 2023; Iyoha *et al.*, 2024). Using information on suppliers' parent companies from S&P Global Market Intelligence, we find that less than 1% of suppliers involved in maritime shipments from Mexico and Vietnam to the U.S. have a Chinese parent. For Vietnam, this number increased from 0.4% in 2016 to 0.7% in 2023. For Mexico, it hovered around 0.3%-0.5% during this period. The role of potential re-exporting (rerouting/transshipment) via Chinese-owned multinationals' offshore subsidiaries is thus limited in our estimates based solely on maritime shipments.

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 information on commercial and industrial (C&I) loans above $1 million. The data are collected on a quarterly basis from about 40 large bank holding companies (BHCs) subject to stress tests (that is, with more than $100 billion in total consolidated assets). These data cover close to three-quarters of total U.S. C&I loans to U.S. non-financial firms (Chodorow-Reich *et al.*, 2022). 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 committed amount). Furthermore, we observe contractual features such as the interest rate (set to zero for credit lines that are fully undrawn and dropped from the analysis), loan 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 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 over the full time period. We also exploit information on U.S. firms' ultimate corporate parent names from S&P Global Market Intelligence, which allows the matching of additional 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 in a banking relationship at the end of 2017.[8]

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). For 10-digit HS products and each tariff-targeted country, these data report 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 several 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 tilted 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 abroad) and publicly listed. They are also larger, have less cash, and lower leverage than

[8] 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.

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 undiversified and 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, in firm-product-country data, we compute the mean, median, and maximum number of source countries and of individual suppliers for each HS 6-digit product and firm; then, we report the median, 75th percentile and 95th percentile statistics in the cross-section of firms. As seen in Panel A of Table 1, the median U.S. firm sourced products from a single country in both years. At the 95th percentile, firms imported from an average of 2.9 countries in 2016 and 2.4 countries in 2022. For comparison, estimates in Antras *et al.* (2017) reveal a similarly undiversified base of source countries in 2007 at the HS 10-digit product level. At face value, these estimates suggest diversification has slightly declined since the mid-2010s. In Panel B of Table 1 we turn to the number of individual suppliers within HS 6-digit product and within country. These statistics, too, show a decline in diversification, with the firm at the 75th percentile importing a given product from a given country from a maximum of 3 suppliers in 2016 versus 2 suppliers in 2022. In addition, the median firm continues to have one supplier (per country and product).[9]

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 lessening the 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 (in 2016–2017) that was subject to tariffs in 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

[9] Similar statistics hold for the larger sample of unmatched U.S. importers—see Table A1.

firms were also affected by tariffs, highlighting the wide-ranging nature of the China tariffs.[10] A key concern is that potential differences across the two groups of firms could drive access to external finance and capacity to diversify. However, the diagnostic tests in Table A5 show that 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 Supplier Search Costs

We start the analysis by showing that the realignment of global supply chains after the 2018–2019 tariffs entails sizable costs, comprising both the direct cost of tariffs and the additional search costs of finding new suppliers. These costs explain why bank financing is a critical driver of the likelihood and speed at which tariff-hit importers expand their geographical diversification. We begin by presenting a conceptual framework which rationalizes the role of specialized banks in providing credit and facilitating supply chain realignment. Then, we provide evidence at the firm-product level of (a) exit from relationships with Chinese suppliers and entry into relationships with suppliers from Asian countries (ex-China), and (b) the search costs faced by firms in finding new suppliers.

3.1 Conceptual Framework

Our empirical analysis follows the conceptual framework outlined in Appendix A-I, which considers the fixed cost of setting up new supplier relationships in a foreign market and the role of specialized banks in reducing this cost. The existing supplier in region j offers intermediate goods at price $p_{j,t}$, which includes an import tariff $\tau_{j,t} \geq 1$. The probability of switching from the existing supplier to a new supplier in a different region k depends on the

[10] The academic literature sees the 2018–2019 tariffs as largely unanticipated (Grossman *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.

relative expected value of the new supplier relationship, net of the cost of switching $C_{k,t}$:

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

The fixed cost of switching suppliers can be financed by two types of banks: specialized banks and other banks. Specialized banks are able to offer relatively more favorable lending terms thanks to informational advantages in particular countries (as discussed in detail in Section 5). Firms can raise capital F_j that would cover costs associated with gathering information about suppliers located in region j and any other sunk costs like legal fees. The cost of raising capital r_j includes banks' advisory fees and interest rate, both of which are lower for banks specialized in region j.

This framework delivers two testable predictions. First, the probability of switching to a new supplier increases with higher tariffs, which guides our analysis of how tariffs affect the formation of new supplier relationships outside China. Second, the probability of switching increases as the cost of financing and advisory services offered by banks decreases. This prediction informs our analysis of the role that specialized banks can play in shaping supply chain realignment.

3.2 Supply Chain Realignment

We examine 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, specifically, China and Asia ex-China:

$$\text{Trade Outcome}_{ipt} = \exp[\beta_1 \text{Tariff-hit}_{ip} \times \text{Post}_t + \beta_2 X_i \times \text{Post}_t + \sigma_{ip} + \theta_{pt} + \phi_{kt} + \mu_{st}] + \epsilon_{ipt}, \tag{2}$$

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 trade volumes.[11] An exit from a supplier relationship is identified as a firm stopping imports from a supplier in a given year, conditional on importing from that supplier in the previous year. A supplier entry occurs when a firm begins importing from a new supplier in a given year, conditional on not having sourced from that supplier in the previous year. Within-product changes in the number of suppliers are calculated as differences between two consecutive years.[12] The tariff-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 foreign 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

[11] 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 2 (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).

[12] 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 importer is observed as active.

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 not all firms replaced a Chinese supplier with a new Asian supplier. As U.S. importers respond to the 2018–2019 tariffs by churning suppliers across countries, the import share from China 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 A13), (b) adding a firm-specific correction for potential pretrends as in Autor *et al.* (2024) (Table A14), (c) exploiting the staggered timing of tariffs (Table A18), (d) dropping publicly-listed firms (Table A21) or importers from the wholesale and retail sectors from the regression sample (Table A23), and (e) examining the sample of U.S. importers in Panjiva not matched to Y14 (Table A2). See Appendix A-V for a detailed presentation of robustness checks.

3.3 Evidence on Search Costs

To provide more direct evidence on the costs of searching for new suppliers, we document that the time needed to find new suppliers varies 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:

$$\lambda_{ip}(t) = \lambda_0(t) \exp\left[\xi X_{ip} + \nu_k + \delta_l\right], \tag{3}$$

where $\lambda(t)$ is the expected hazard in quarter t for a given firm i-product p 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 2 (size, leverage, liquidity, ROA, and retaliation tariff dummy) and firm-level credit demand obtained using the methodology of Amiti and Weinstein (2018).[13] We also include industry and state fixed effects (ν_k and δ_l).

Unlike our previous regressions spanning the period between 2016 and 2019, here we extend the Post period through the end of 2022 to allow firms more time to find new suppliers after the introduction of the tariffs. Over the 20-quarter interval of this extended Post period, the average importer takes 11.7 quarters to match to a new supplier in Asian countries outside China (the median is 12 quarters and 75th percentile is 17 quarters).

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). Panel A of Table 4 reports the hazard ratios estimated based on Equation 3 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

[13] 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. 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).

new Asian supplier that is 17% to 25% higher than high-stickiness relationship firms.[14]

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. Ex-ante diversified firms should have superior knowledge about the region and should face lower search costs. The coefficient estimates reported in Panel B of Table 4 are significant and economically sizable, indicating that prior supplier relationships in Asia significantly raise the odds of finding new suppliers after the tariffs. Hazard ratio estimates indicate that ex-ante diversified firms match to new suppliers about three 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 channels, we turn to the role of banks.

4 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:

$$\text{Bank Credit Outcome}_{ibt} = \delta_1 \text{Tariff-hit}_i \times \text{Post}_t + \delta_2 X_i \times \text{Post}_t + \alpha_i + \varphi_{kst} + \kappa_{bt} + \tau_{ib} + \epsilon_{ibt}, \quad (4)$$

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

[14] The corresponding Kaplan-Meier failure functions for two types of firms are reported in Panel A of Figure A3, which shows that, after the tariff shock, low-stickiness firms are more likely to match to a new supplier than high-stickiness firms.

[15] The average credit line utilization rate is 35% and the median interest rate is 3.75% (Table 2). We also estimate Equation 4 restricting the control group to importers, see Appendix A-V.

Post dummy and the set of controls X_i are the same as in Equation 2. 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 potentially 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 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 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 do not normally renege on pre-committed lines of credit unless the firms' creditworthiness signficantly deteriorates and/or it violates covenants (Roberts and Sufi, 2009; 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, see 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 induce an upward bias in 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 A4). Table A10 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 A13). 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 A15). Third, our results are insensitive to restricting the control group only to importers (Table A16) and to controlling for relationship banking with the end-2017 loan share as a measure of bank-firm relationship intensity (Table A17). Fourth, our results hold up to dropping all loans to publicly-listed firms and to multinational firms based on an alternative definition (Tables A21-A22).

5 Role of Specialized Banks

So far, our results show that tariff-hit U.S. importers pared back their 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 frictions associated with trade search costs. Here, we test the second conjecture of the framework in Appendix A-I that the probability of switching to a new supplier decreases with the switching cost. This switching cost would be lower for tariff-hit firms borrowing from specialized banks if such banks offered more favorable loan terms (a *credit* channel) and/or information about potential suppliers (an *information* channel). Our tests provide evidence of the value of relationships with specialized banks in lessening supply chain realignment.

5.1 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 (Matray *et al.*, 2024) 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] The banks

[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 gathers data on the distribution, by country, of claims on foreigners held by certain U.S. banks.

selected as "specialized" according to this measure provide loans to 43% of importers and account for 37% of total lending volume (39% of credit line commitments) in Y14 dataset. In addition, the selected specialized banks have foreign subsidiaries and correspondent banking relationships across different Asian countries, a source of variation we are going to exploit to document the information channel.

As discussed below, we subject our baseline measure of specialization to two tests. The first test checks that the specialization measure captures the benefits of borrowing from a bank specialized *in Asian markets* and not just a bank with global business model. The second test verifies that the results are robust to a specialization measure that captures banks' lending orientation toward firms engaged in trade activities with Asian countries.

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 A6, specialized banks are indeed slightly larger than other non-specialized banks, reflecting their global nature. However, all other characteristics—leverage, core deposit share, profitability, overhead expenses, and asset quality—are statistically indistinguishable between the two types of banks. Second, the firms borrowing from specialized banks—with outstanding loans from at least one specialized bank during 2016–2017—may be different from those borrowing from other banks. However, this does not appear to be the case, as the two groups of firms are similar in terms of key balance sheet characteristics and lending outcomes (Table A7).

5.2 Credit Channel of Specialized Banks

We test for differential effects in bank borrowing by tariff-hit importers using the specification in Equation 4 for loan interest rates and breaking down the DiD coefficient by specialized 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 than 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. These pricing results suggest that specialized banks may view their tariff-hit borrowers as less risky than non-specialized banks, which we confirm by examining changes in borrower probabilities of default. Using internal risk ratings-based models verified by supervisors, Y14 banks estimate and report one-year ahead probability of default for their borrowers. Indeed, as shown in Column 2 of Table A9, tariff-hit firms with specialized banks are, on average, assessed as having lower default risk than they are assessed by non-specialized banks.[17]

Placebo Test. To address the possibility that our bank specialization measure captures the benefits of borrowing from a global bank rather than a bank specialized in Asia, we perform a placebo test that replaces Asian with European specialization. Here, specialized banks have 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 show no advantage of banking with a Europe-specialized bank for tariff-hit firms, confirming 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 A13), (b) control for relationship banking (A17), and (c) change the definition of bank specialization to refer to banks with outsized lending exposure to trade-oriented firms using a definition of bank specialization from Paravisini *et al.* (2023) (Table A19)—see Appendix A-V.

[17] Exploring additional margins of lending, we find that tariff-hit firms with specialized banks receive loans with longer maturity than tariff-hit firms with other banks (Table A9, Column 1). 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 A9 and Table A10, respectively), consistent with the theory of specialized lending in Blickle *et al.* (2024).

5.3 Information Channel of Specialized Banks

We start by showing that firms with specialized banks are more likely to find new suppliers in Asia. Then, we document the role of specialized banks in reducing informational asymmetries in foreign markets using two approaches. First, we use information on local bank presence across Asian countries to determine if the probability of a match is higher in those countries where a firm's specialized bank also has foreign affiliates. Second, we leverage data on foreign subsidiary income statements to compare changes in foreign subsidiary income from advisory services between Asian and non-Asian subsidiaries of specialized banks. We continue to exclude multinational firms from the sample to allay any potential concerns that the evidence on the information channel is driven by firms' own network effects.

Network Effects. By serving foreign markets, specialized banks gather local market knowledge and information about customer networks outside the U.S. Such information is more easily acquired when a bank operates local bank branches and subsidiaries. To test for "local bank network effects" in the process of matching to new Asian suppliers, we examine if the odds of matching to new suppliers in a particular country are higher for firms whose specialized bank also has foreign affiliates in that same country. Our approach is similar to Brancati (2022), who shows that the odds of entering new export markets is significantly higher for firms whose commercial bank has a foreign branch in that market. We measure banks' local presence with a dummy for those banks with positive local claims, which imply that the bank is actively lending to residents in that country. Furthermore, we restrict our attention to the top six Asian countries where U.S. importers find new suppliers after the imposition of tariffs (and refer to these countries as "new supplier countries"), which account for almost half of new supplier matches. For each country, we determine if each specialized bank is present locally and then define a dummy taking value one for those U.S. importers in a relationship with a specialized bank that is present in that country. Then, we stack the data in a panel at the firm-product-new supplier country-quarter level.

Cox proportional hazards regressions shown in Table 7 evaluate the role of local bank network effects in improving U.S. importers' odds of matching to new Asian suppliers. Coefficient 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 4.6% in Column 3, corresponding to the most saturated specification) compared to tariff-hit firms which borrow from other banks.[18]

To shed light on the reason why specialized banks can facilitate supply chain realignment of their client firms, we exploit information about their local presence. Estimates in Panel B of Table 7, based on the stacked panel that organizes the new suppliers by country, show that the odds of finding new Asian suppliers in countries where a specialized bank is also present are 10% to 15% higher for firms in credit relationships with that specialized bank. This result supports the notion of an information channel by which specialized banks leverage their knowledge of local conditions and networks to help their client firms find new suppliers.

Banks' ability to acquire knowledge about local markets and to intermediate information about potential suppliers can also be measured based on the banks' lending activities and business ties to local banks. Thus, we explore alternative ways of capturing bank "network effects" based on a banks' previous syndicated lending to firms and its connections to correspondent banks in a particular country.[19] The results in Table A12 are consistent with network effects: local bank networks captured via prior syndicated lending activities and relationships with local correspondent banks in a given country increase the odds of a specialized banks' borrowers matching to a new supplier in that same country by at least 8% (panel A, Column 1) or 9.5% (panel B, Column 2), respectively.[20]

[18] The corresponding Kaplan-Meier failure functions for two types of firms are reported in Panel B of Figure A3, which show that, after the tariff shock, firms borrowing from specialized banks are more likely to match to a new supplier than firms which borrow from other banks.

[19] To pin down past syndicated lending activities, we use loan origination data from Thomson Reuters LPC DealScan over the ten years preceding the 2018–2019 rise in trade tensions (2008–2017) and identify those specialized banks that lent to financial and non-financial companies in each of the six new-supplier countries of interest. Similarly, we use data from LexisNexis Global Payments Resource Bankers' Almanac to identify the foreign countries where each specialized bank has correspondent banking relationships.

[20] We obtain similar results when the definition of bank specialization refers to banks with lending portfolios tilted towards borrowers engaged in imports/exports with firms in Asian countries (Paravisini

Value of Relationships with Specialized Banks. The specifications in Table 7 enable us to quantify the value of relationships with specialized lenders insofar as they help reduce the time to finding new suppliers. Using the estimates in Panel A of Table 7, the difference in hazard ratios between firms with and without specialized banks ranges between 4.6% and 8.5%. Given that the average time it takes a firm to match with a new Asian supplier is 11.7 quarters, firms with specialized banks will be between $4.6\% \times 11.7 \times 3 = 1.6$ months and $8.5\% \times 10.7 \times 3 = 2.9$ months faster than other firms to connect to new Asian suppliers. Turning to the added benefit of working with a specialized bank that is present in particular countries where U.S. importers seek new suppliers, the estimates in Panel B of Table 7 show that the difference in hazard ratios between firms with specialized banks with and without presence across such countries ranges between 10.2% and 15.9%. Therefore, it is between $10.2\% \times 11.7 \times 3 = 3.6$ months and $15.9\% \times 11.7 \times 3 = 5.6$ months relatively faster for firms with specialized banks with local presence in a particular country to connect to Asian suppliers in that same country.

Advisory Fees. We can also test the information channel by exploiting variation in the locations of foreign subsidiaries of U.S. banks. To the extent that specialized banks leverage their informational advantages and provide advisory/consulting services to their client firms, then the information channel would predict that the Asian offices of a specialized bank should have stronger advisory fee income growth than its other, non-Asian, offices. To test this idea, we gather quarterly income statement data for foreign subsidiaries of U.S. banks and estimate a DiD specification that allows for differences in advisory fee income growth by subsidiary location (within parent bank).[21]

Table 8 reports the results. Positive and statistically significant estimates on the DiD term "Post×Asian subsidiary" in Columns 1-2 suggest that Asian subsidiaries grew their fee-

et al., 2023)—see Table A20 and related discussion in Appendix A-V.

[21] 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.

based income faster by 1.3% during the 2018–2019 period than subsidiaries located elsewhere (within parent bank). Columns 3–4 break down this coefficient by subsample of specialized versus non-specialized parent banks. The results reveal significant effects for both types of parent banks, although the coefficient estimates are larger for specialized parent banks, indicating growth of 2%–2.4%, and thus higher than that of other banks with 1.3%.[22]

In conclusion, the evidence of (a) network effects in the formation of new trade relationships and (b) relatively higher income growth at Asian foreign offices of specialized banks overall supports the notion of banks facilitating the realignment of global supply chains through the provision of information.

5.4 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 2), 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 that Europe-specialized banks improve 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.

[22] Our results on foreign subsidiaries' advisory fees should be interpreted as suggestive given the following caveats. First, in the most saturated specification (Column 4), the difference between specialized and other parent banks is significant only at the 12% level. Second, a more granular breakdown of fee-based income by type of activity is not available in the data, so we are not able to disentangle subsidiary income that comes from a particular type of consulting services versus other fee-based activities such as investment banking, mergers and acquisitions, and securities brokerage. Third, the FR 2314 data only cover the income statements of U.S. banks' foreign subsidiaries and not their foreign branches.

6 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 input sourcing from Chinese suppliers to other Asian countries, U.S. importers face salient search costs. *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 U.S. banks with expertise in the provision of trade finance services in Asia eased both 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 establish new trade relationships faster. We estimate that it takes close to three years for the average importer to match to a new supplier in Asian countries outside China, for a given narrowly-defined product, and this time is significantly reduced when the importer's bank has expertise in trade finance services to Asian markets.

Our results emphasize the importance of banks, especially specialized banks, in absorbing supply chain shocks and limiting their macroeconomic consequences. They also provide an explanation for the relative speed of the "great reallocation" of global value chains after the 2018–2019 tariffs. Some caution is needed in using our estimates to calibrate bank and firm responses to shifts in trade policies in different economic environments, as our sample period had low interest rates and strong bank and firm balance sheets. These estimates can nevertheless serve as a benchmark for evaluations of the cost of reconfiguring supply chains for private companies and the important role of commercial banks in meeting this cost.

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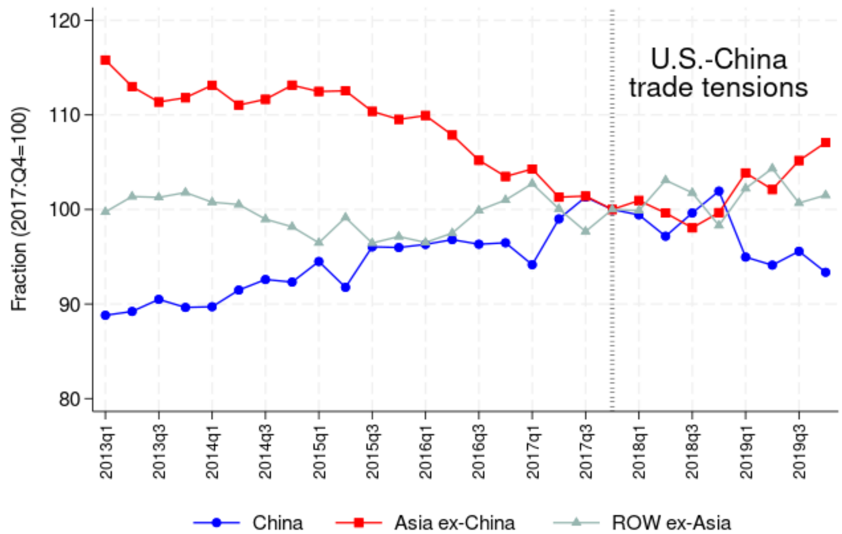
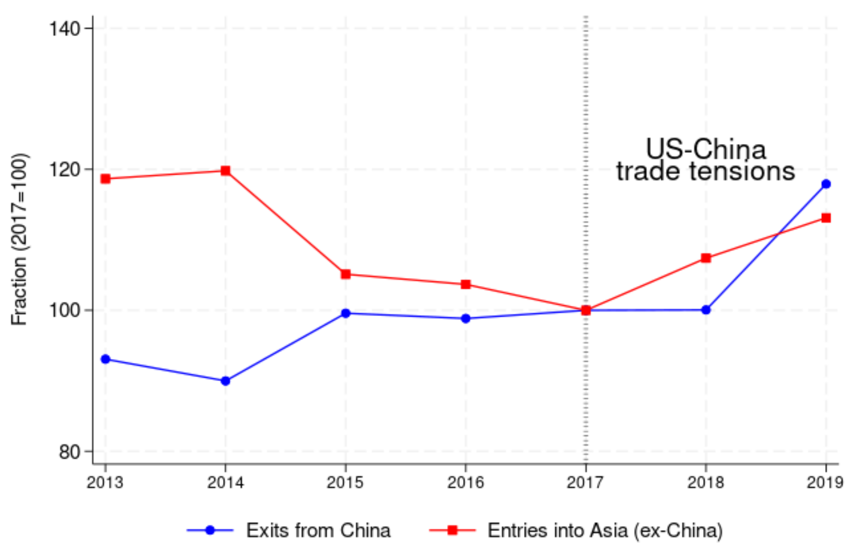
Figure 1: **Supply chain reconfiguration and U.S.-China trade tensions**

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: **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. The sample includes all matched importers. 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, median, 75th percentile 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			
Median	2016	1.0	1.0	1.0
	2022	1.0	1.0	1.0
75th percentile	2016	1.3	1.0	2.0
	2022	1.0	1.0	1.0
95th percentile	2016	2.9	3.0	4.0
	2022	2.4	3.0	3.0
	(B) Number of suppliers			
Median	2016	1.0	1.0	1.0
	2022	1.0	1.0	1.0
75th percentile	2016	2.0	2.0	3.0
	2022	1.7	2.0	2.0
95th percentile	2016	6.6	7.0	10.0
	2022	5.5	6.0	8.0

Table 2: **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
(C) Foreign bank subsidiary-quarter data						
Advisory fee income (over assets)	6364	0.032	0.223	0.000	0.000	0.002
0/1 Asian subsidiary	6364	0.171	0.377	0.000	0.000	0.000
0/1 Specialized parent bank	6364	0.107	0.309	0.000	0.000	0.000
Subsidiary size (log-assets)	6364	14.919	1.567	14.123	14.762	15.721

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 2. 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 3. 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. 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 3 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 new supplier in Asia**			
	(A) Relationship stickiness			
0/1 Firm with low-stickiness relationships	1.2513***	1.2383***	1.1651***	1.1571***
	(0.0155)	(0.0215)	(0.0192)	(0.0191)
Observations	1,348,224	729,697	729,697	729,455
Firm controls	Y	Y	Y	Y
Firm credit demand (Amiti-Weinstein)	-	Y	Y	Y
Industry FE	-	-	Y	Y
State FE	-	-	-	Y
	(B) Prior experience in Asia ex-China			
0/1 Firm with prior suppliers in Asia	3.0684***	3.1389***	2.9559***	2.9511***
	(0.0967)	(0.1415)	(0.1365)	(0.1310)
Observations	1,435,779	778,132	778,132	777,890
Firm controls	Y	Y	Y	Y
Firm credit demand (Amiti-Weinstein)	-	Y	Y	Y
Industry FE	-	-	Y	Y
State FE	-	-	-	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 4. 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^2	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%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **Loan interest rate**	(4) **Credit line utilization**	(5) **Loan interest rate**	(6) **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^2	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 3. In panel A, the data are at the firm-product-quarter level and in panel B they are at the firm-product-new supplier country-quarter level over 2018–2022. In the panel A, the dependent variable represents the odds for a tariff-hit firm of finding a new supplier in Asia (ex-China). In panel B, the dependent variables represent the odds for a tariff-hit firm of finding a new supplier in a given country in Asia (specifically, India, Indonesia, Japan, South Korea, Thailand, or Vietnam) where the importer's specialized bank has local presence. Local presence is defined as referring to banks with positive local claims (that is, the bank makes loans in foreign or domestic currency to local residents) in 2016–2017, sourced from FFIEC 009 form. 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). 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 3 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 a new supplier in Asia**			
0/1 Firm with Specialized Bank	1.0570***	1.0848***	1.0455*	1.0581*
	(0.0223)	(0.0294)	(0.0280)	(0.0310)
Observations	1,227,736	731,698	731,698	731,698
Firm controls	Y	Y	Y	Y
Firm credit demand	-	Y	Y	Y
Industry FE			Y	Y
State FE	-	-	-	Y
	(B) Odds of finding a new supplier in Asia in a country where specialized bank is present			
0/1 Firm with Specialized Bank with Local Presence	1.1050**	1.1585***	1.1531***	1.1016*
	(0.0433)	(0.0590)	(0.0623)	(0.0611)
Observations	532,821	322,015	322,015	322,015
Firm controls	Y	Y	Y	Y
New supplier country FE	Y	Y	Y	Y
Firm credit demand	-	Y	Y	Y
Industry FE	-	-	Y	Y
State FE	-	-	-	Y

Table 8: **The information channel of specialized banks: Advisory fees**

This table reports OLS estimates from a regression that examines changes in advisory fee income of Asian subsidiaries of specialized U.S. banks during 2018–2019 compared to 2016–2017. The data are at the subsidiary-parent bank-quarter level during 2016–2019. The dependent variable represents advisory fee income (as share of assets) from the income statement of the bank subsidiary. We define advisory fee income to include investment banking, advisory, brokerage, underwriting fees and commissions, and other non-interest income. "Asian subsidiary" is a dummy variable taking value one for foreign subs that are located in Asia. "Specialized parent bank" is a dummy variable taking value one for the U.S. banks with positive cross-border trade finance claims on non-financial firms in Asia (ex-China). "Post" is a dummy variable taking value one during 2018–2019 and zero during 2016–2017. The specifications include foreign subsidiary size (log-assets) as a control variable. Standard errors are clustered on parent bank. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Advisory fee income**			
Post × Asian subsidiary	0.0137***	0.0134***		
	(0.0043)	(0.0038)		
Post × Asian subsidiary × Specialized Parent Bank [1]			0.0246***	0.0207***
			(0.0009)	(0.0046)
Post × Asian subsidiary × Other Parent Bank [2]			0.0127**	0.0127***
			(0.0046)	(0.0041)
Observations	6,364	6,364	6,364	6,364
R^2	0.4642	0.4643	0.4642	0.4643
p-value t-test Ha: $\|1\| > \|2\|$			0.015	0.119
Foreign subsidiary size	Y	Y	Y	Y
Parent bank × Quarter FE	Y	Y	Y	Y
Foreign subsidiary FE	-	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%.

Dependent variable:	(1) **0/1 Entry into Asia**	(2) **# Asian suppliers gained**	(3) **Asian import share**	(4) **0/1 Entry into Asia**	(5) **# Asian suppliers gained**	(6) **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"

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A-I Conceptual 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 region and ii) banks specialized in that region, 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 in region 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:

$$V(p_{j,t}) = \max_k \pi(p_{j,t}) + \beta \mathbb{E}[V(p_{j,t+1})] + \mathbb{E}_\epsilon \underbrace{\left[\epsilon_{k,t} + \beta \int_{p_k^{min}}^{p_k^{max}} [V(p_{k,t+1}) - V(p_{j,t+1}) - C_{k,t}] dG(p_k) \right]}_{\text{expected value of switching suppliers}}, \tag{5}$$

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 costs associated with switching suppliers 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:

$$\mathbb{E}(C_j) = \delta r_j F_j + (1 - \delta) r_k F_j, \tag{6}$$

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:

$$\lambda_{jk,t} = \frac{\exp[\mathbb{E}(V(p_{k,t+1}) - V(p_{j,t+1}) - C_{k,t})]}{\sum_{j',k'} \exp[\mathbb{E}(V(p_{k',t+1}) - V(p_{j',t+1}) - C_{k',t})]}. \tag{7}$$

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 7, 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's match declines in price, the probability of switching to a new supplier increases with tariffs $\tau_{j,t}$:

$$\frac{\partial \lambda_{jk,t}}{\partial \tau_{j,t}} > 0. \tag{8}$$

This first prediction underpins the empirical specifications in Section 3.2, 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.

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

$$\frac{\partial \lambda_{jk,t}}{\partial r_k} < 0. \tag{9}$$

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 5.4, 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 between the Panjiva ID and the Capital IQ identifier (CIQ) from S&P Global Market Intelligence, along with information on the ultimate parent name and country. 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 about 769,000 importers. The matching procedure yields a total number of about 32,000 importers, out of which we see bank loans and financial statement information for 26,188 importers. Furthermore, we match to the Y14 a total of 11,431 exporting firms, which allows us to identify the importers that also have exporting activities and whose export products are subject to retaliatory tariffs (a baseline control variable). The Y14-matched importers account for close to 20% of total shipments and total import volume from China and the Asia and Pacific region in 2007.

In Appendix A-III we describe the basic characteristics of U.S. importers using balance sheet data from Y14.

Matched versus unmatched importers. We show that the levels of supply chain diversification of matched importers, reported in Table 1, are similar to those of unmatched importers, reported in Table A1. The median importer in both samples imports from one country and one supplier. However, we see differences in the right tail of the firm distribution. Compared to the firm at the 75th and 95th percentiles in the matched sample,

Table A1: **Firm-level within-product diversification: Unmatched Importers**

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. The sample includes all unmatched importers. 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, median, 75th percentile 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			
Median	2016	1.0	1.0	1.0
	2022	1.0	1.0	1.0
75th percentile	2016	1.0	1.0	1.0
	2022	1.0	1.0	1.0
95th percentile	2016	2.0	2.0	2.0
	2022	1.7	2.0	2.0
	(B) Number of suppliers			
Median	2016	1.0	1.0	1.0
	2022	1.0	1.0	1.0
75th percentile	2016	1.0	1.0	1.0
	2022	1.0	1.0	1.0
95th percentile	2016	3.0	3.0	4.0
	2022	2.9	3.0	4.0

unmatched firms tend to be less diversified. This difference suggests that the matched sample includes larger importers that are likely to be clients of Y-14 reporting banks compared to the universe of Panjiva importers.

We also show that the main supply chain reallocation results are similar for matched and unmatched importers. In Table A2, we report the estimation results of specifications similar to Table 3 but estimated separately for the two groups of firms. For the unmatched firms we do not have industry classification and balance sheet data, which are omitted from the specifications. Even without the full set of controls, the results closely mirror those of the

Table A2: **Supply chain reallocation: Matched vs. Unmatched Importers**

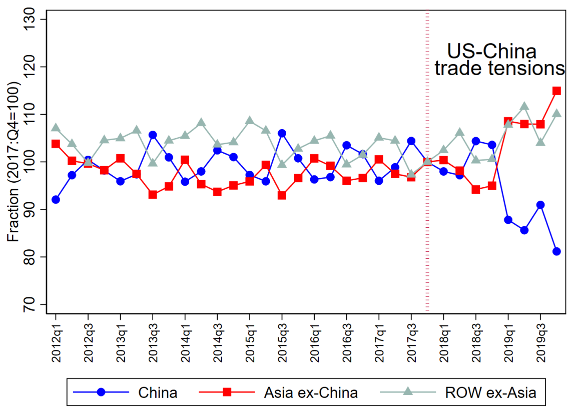
This table reports PPML estimates from a regression of trade outcomes on the tariff-hit dummy variable interacted with the Post dummy. Sample specifications are the same as in Table 3 but the sample includes all firms in the Panjiva dataset (not necessarily matched to the Y14), therefore firm controls and (NAICS) 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**
	Realignment from China			**Realignment to Asia (ex-China)**		
	(A) Y-14 Matched Importers					
Tariff-hit × Post	0.6220***	0.6093***	-16.3917***	0.6492***	0.5545***	0.0273***
	(0.0615)	(0.0812)	(0.0886)	(0.0135)	(0.0160)	(0.0061)
Observations	348,240	348,240	183,910	311,751	311,751	164,096
	(B) Non-matched Importers					
Tariff-hit × Post	0.1280***	0.0951***	-0.0600***	0.2362***	0.2007***	0.0666***
	(0.0088)	(0.0103)	(0.0048)	(0.0073)	(0.0099)	(0.0043)
Observations	803,096	803,096	622,826	742,367	742,367	563,471
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

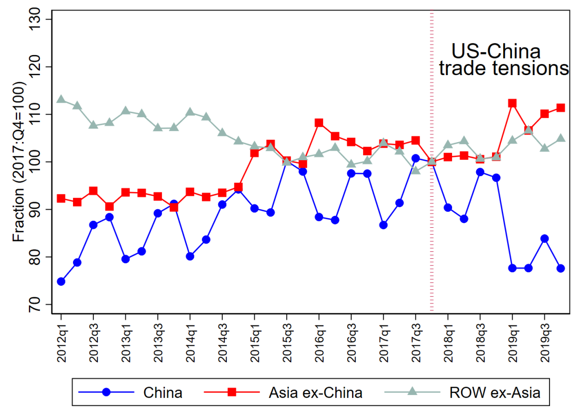
matched sample. However, the coefficient magnitudes of the DiD term Tariff-hit×Post for unmatched firms are smaller than those for matched firms, suggesting this sample contains smaller and more constrained firms (Panel B). Despite the specification differences, the signs of all estimated coefficients are as expected, with tariff-hit firms reducing the number of Chinese suppliers and initiating new supplier relationships in Asia outside China after the 2018–2019 tariffs.

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 and are based on shipments to all ports. 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

Firm's name redactions in Panjiva. Despite the fact that Panjiva only contains information on maritime shipments, the 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. Nevertheless, 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 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 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).

The redaction problem in Panjiva implies that our results should be interpreted with caution. 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 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 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 A3 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).

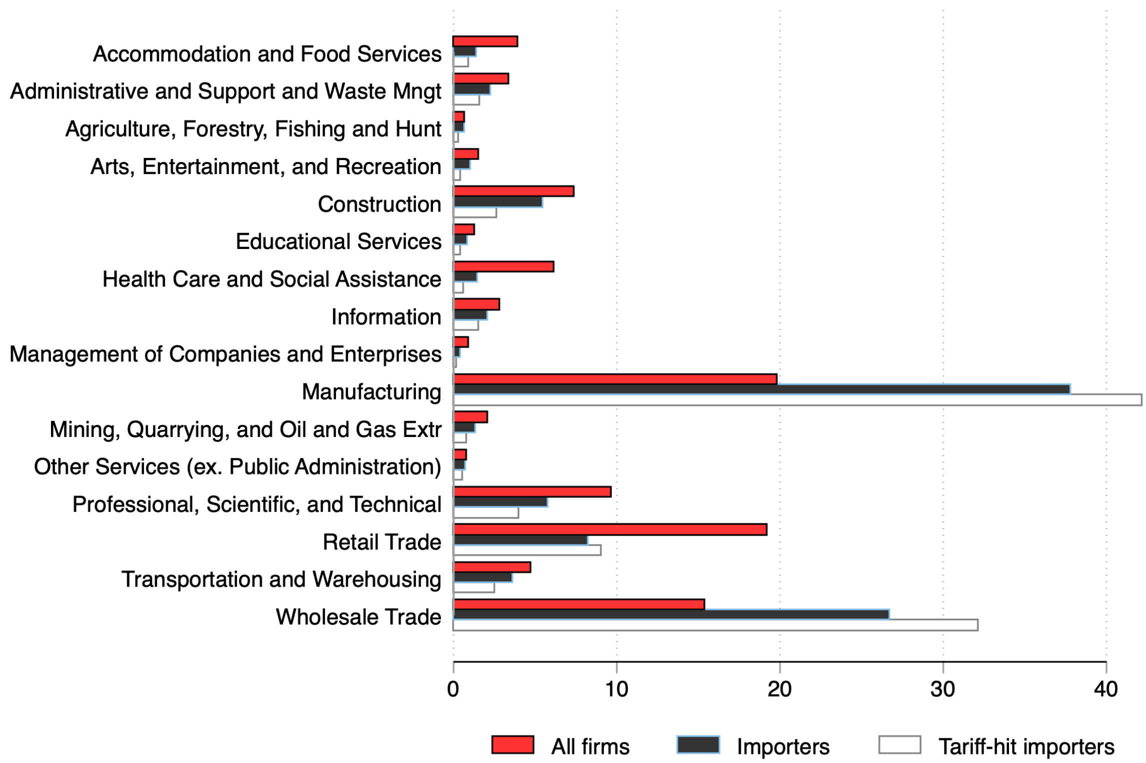
Table A3: **Importer characteristics**

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 A4: **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 A15). 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 A5: **Covariate balance 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 (2)-(1)**
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 A6: **Covariate balance 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 A7: **Covariate balance 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 (2)-(1)**
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 A8: **Covariate balance 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 (2)-(1)**
	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 A9: **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^2	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 A10: **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^2	0.9108	0.9452	0.9626
Bank controls	Y	Y	Y
Quarter FE	Y	Y	Y
Bank FE	Y	Y	Y

Table A11: **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^2	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 A12: **The information channel of specialized banks: Network effects based on alternative measures**

This table reports Cox proportional hazards model estimates based on Equation 3. The data are at the firm-product-new supplier country-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 variable represents the odds for a tariff-hit firm of finding a new supplier in a given country in Asia (specifically, India, Indonesia, Japan, South Korea, Thailand, or Vietnam) where the importer's specialized bank has local presence, defined as having supplied syndicated loans to financial and nonfinancial firms during 2008–2017 (using data from Thomson Reuters LPC DealScan) in panel A or as having correspondent banking relationships (using data from the LexisNexis Global Payments Resource Bankers' Almanac) in panel B. 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). 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 3 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%, #15%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Odds of finding a new supplier (A) ... in a country where the specialized bank has provided syndicated lending**			
0/1 Firm with Specialized Bank With Local Syndicated Lending	1.0796**	1.1772***	1.1478***	1.1016*
	(0.0393)	(0.0555)	(0.0573)	(0.0572)
Observations	532,821	322,015	322,015	322,015
Dependent variable:	**(B) ... in a country where the specialized bank has correspondent banking relationships**			
0/1 Firm with Specialized Lender With Local Correspondent Banking Relationships	1.2844***	1.0949#	1.1106#	1.0686
	(0.0623)	(0.0665)	(0.0717)	(0.0683)
Observations	532,821	322,015	322,015	322,015
Firm controls	Y	Y	Y	Y
New supplier country FE	Y	Y	Y	Y
Firm credit demand	-	Y	Y	Y
Industry FE	-	-	Y	Y
State FE	-	-	-	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; (f) and the robustness of the baseline results to the exclusion of wholesale and retail sectors, and that of publicly listed firms or multinational firms based on an alternative definition.

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 A5, A6, and Table A7 of covariate balance 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 A13 shows coefficients that are virtually identical to those in Columns 1-2 in Table 5 and Panel B of Table 3. If anything, 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 A13 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 2 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 A14 shows that the pre-trend variable is precisely estimated in all cases, but the DiD coefficient of interest "Tariff-hit × 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 4 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 A15). 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 A15 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 A15, 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×Post" by quarter. The visual inspection of the quarterly dynamic DiD coefficients—plotted in Figure A4—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 A16 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.

Role of Relationship Banking. In Table A17 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 A18. 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). We check that our results are robust to an alternative bank specialization measure that captures banks' orientation toward particular borrowers such as trade-oriented firms, specifically importers from and exporters to Asian countries. Following the approach in Paravisini *et al.* (2023), we define specialized banks as those banks with a high weighted loan portfolio share to borrowers engaged in imports/exports with firms in Asian countries (above the 75^{th} percentile of the portfolio share distribution). To obtain this measure, we compute, for each borrower, (a) its total trade volume (imports + exports) on yearly frequency and (b) the share of outstanding debt it has with each bank. Bank specialization in trade with Asia (ex-China) is defined as the bank's borrowers' trade *with Asian countries*, weighted by their debt with the bank, as a share of the bank's borrowers' total debt-weighted trade. The bank specialization measure is thus a weighted loan portfolio share that captures region-specific lending advantage—a bank-specific informational advantage relative to other lenders. We measure specialization as an average over 2016–2017 so it is predetermined with respect to the enactment of tariffs.

The results for this alternative measure of bank specialization are reported in Table A19. In panel A, the estimates indicate that tariff-hit firms with specialized banks increase credit line utilizations by less and obtain cheaper credit than tariff-hit firms with other banks (Columns 1-2). The coefficient magnitudes are higher than those in the baseline analysis (91 bps versus 71 bps for credit lines and 5.3 bps versus 3.6 bps for loan rates). Estimates in Columns 3-5 are also comparable in size to those in the baseline analysis, indicating that tariff-hit firms are more likely to find new Asian suppliers than other firms (significant at the 15% level, Column 4). However, the evidence on specialized banks lessening supply chain realignment is weaker: tariff-hit firms with specialized banks are better able to reallocate, but the differential effects are statistically insignificant (Columns 3–5).

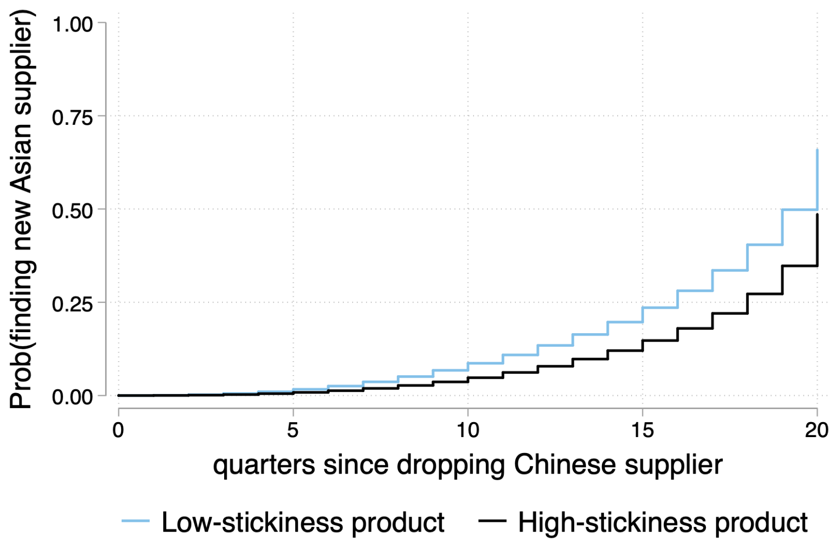
We also employ this alternative measure of bank specialization to check the robustness of our findings on the information channel of specialized banks from Table 7. As shown in Table A20, all our results hold: firms with a specialized banks are between 8% and 11.5% more likely to match to a new supplier in Asia (panel A). In addition, the odds of matching to a new supplier in a particular country in Asia are higher by 8%-15% when the bank specializes in lending to firms who have trade relationships with that same country (panel B).

Publicly-listed Firms and Alternative Measurement of Multinational Firms. We explore the sensitivity of our results to dropping large firms, including multinationals, for which we use an alternative definition based on ownership. In Table A21, 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 A21) compared to 3.6 bps in the full sample (Column 2 of Table 3). In Table A22 we use an alternative approach to identifying multinational firms, which is based solely on the existence of foreign affiliates. In the baseline analysis, we drop from the analysis those firms with at least one shipment from a foreign affiliate during 2016–2019. Now, we classify U.S. firms as "multinationals" if they have at least one establishment abroad, using data on firm ultimate ownership from Dun & Bradstreet for the years 2013, 2016, and 2019. The results continue to remain similar to our baseline analysis when we drop international firms using this alternative method.

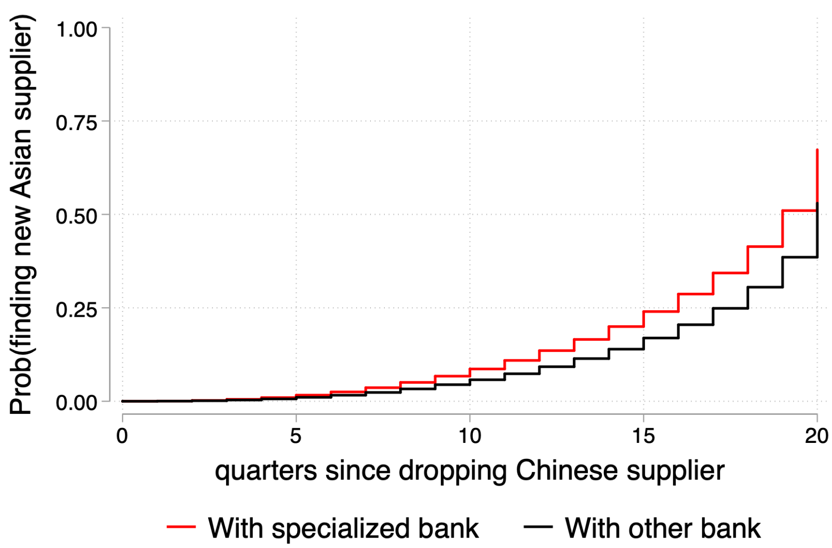
Wholesale and Retail Sectors. Wholesale and retail firms hit by tariffs differ from firms in other sectors (primarily manufacturing, see Figure A2) as they do not engage in production of goods and services. Therefore, these firms are less likely to receive loans for capital investment or research and 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 A23 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).

Figure A3: **Search costs, specialized banks, and reallocation**

Panel A of the figure depicts the probability of finding a new Asian supplier for firms with high vs. low (above/below median) stickiness relationships, using the product-level measure of trade relationship stickiness from Martin *et al.* (2024). Panel B depicts the probability of finding a new Asian supplier for firms in a relationship with specilalized banks vs. other banks. The odds of finding a new Asian supplier are reported on a quarterly basis conditional on the importers dropping a Chinese supplier in the previous quarter. Source: Authors' calculations using data from S&P Panjiva Supply Chain Intelligence and FR Y-14Q.



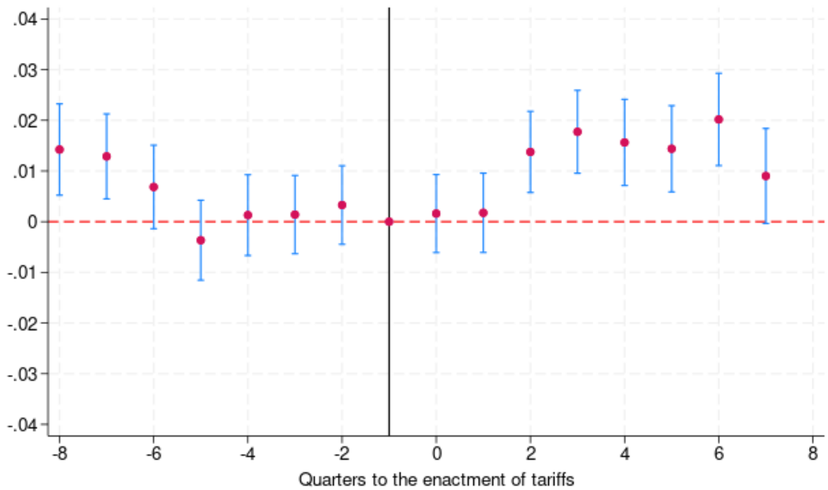
(a) Search costs



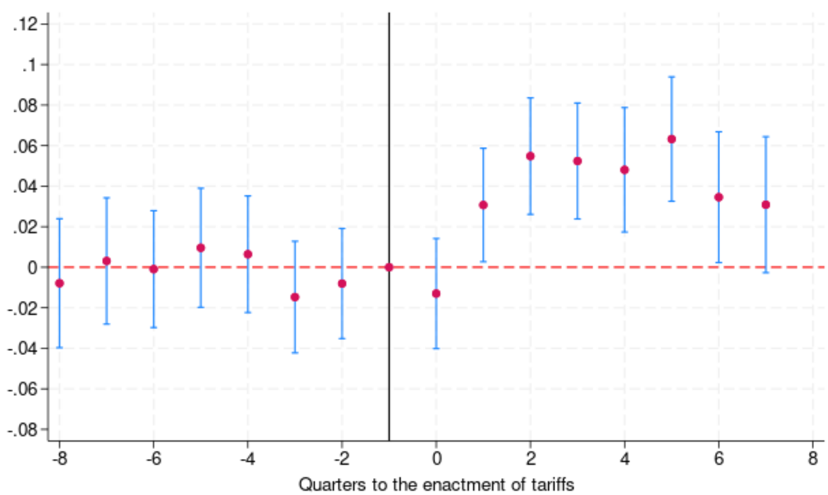
(b) Role of specialized lenders

Figure A4: **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 A13: **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^2	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^2	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 A14: **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 A15: **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%.

Dependent variable:	(1) **Credit line utilization**	(2) **Loan interest rate**	(3) **Credit line utilization**	(4) **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^2	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^2	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 A16: **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%.

	(1)	(2)	(3)	(4)
Dependent variable:	**Credit line utilization**	**Loan interest rate**	**Credit line utilization**	**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^2	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 A17: **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%.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Credit line utilization**	**Loan interest rate**	**Credit line utilization**	**Loan interest rate**	**Credit line utilization**	**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^2	0.7512	0.8048	0.7513	0.8048	0.7513	0.8048
p-value t-test Ha: |1| > |2|					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 A18: **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^2	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^2	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 A19: **Supply chains realignment and bank credit: Alternative measure of bank specialization**

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 × Post" term estimated separately for loans from specialized banks versus other banks using a spline term (there is no omitted category). 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, except that the bank specialization variable is defined referring to banks with outsized lending exposure to trade-oriented firms (importers from and exporters to Asia (ex-China)) during 2016–2017. Bank credit outcomes refer to all outstanding loans. Specialized banks are defined as in Paravisini *et al.* (2023), using the weighted loan portfolio share that captures a region-specific *relative* lending advantage. *** 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)**		
Tariffs-hit × Post × Specialized Bank [1]	0.0027	-0.0000	0.6492***	0.5821***	0.3984***
	(0.0052)	(0.0161)	(0.1351)	(0.1636)	(0.0949)
Tariffs-hit × Post × Other Bank [2]	0.0091**	0.0526***	0.6181***	0.5193***	0.3865***
	(0.0034)	(0.0152)	(0.1660)	(0.1686)	(0.0921)
Observations	772,669	885,195	101,290	101,290	105,881
R^2	0.7585	0.8072	-	-	-
p-value t-test Ha: $\|1\| > \|2\|$	-	-	0.281	0.144	0.338
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 A20: **Information channel of specialized banks: Alternative measure of bank specialization**

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. Specialized banks are defined as in Paravisini *et al.* (2023), using the weighted loan portfolio share that captures a region-specific *relative* lending advantage. The model specifications are the same as in Table 7, except that the bank specialization variable is defined referring to banks with outsized lending exposure to trade-oriented firms (importers from and exporters to Asia (ex-China)) during 2016–2017. *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Dependent variable:	**(A) Odds of finding a new supplier in Asia**			
0/1 Firm with Specialized Bank	1.0829***	1.1155***	1.0806***	1.0941***
	(0.0215)	(0.0293)	(0.0273)	(0.0286)
Observations	1,227,736	731,698	731,698	731,698
Firm controls	Y	Y	Y	Y
Firm credit demand	-	Y	Y	Y
Industry FE	-	-	Y	Y
State FE	-	-	-	Y
	(B) Odds of finding a new supplier in a particular country in Asia			
0/1 Firm with Specialized Bank with Local Presence	1.0859***	1.0861**	1.0844**	1.1518***
	(0.0322)	(0.0387)	(0.0409)	(0.0513)
Observations	625,726	365,382	365,382	365,382
Firm controls	Y	Y	Y	Y
New supplier country FE	Y	Y	Y	Y
Firm credit demand	-	Y	Y	Y
Industry FE	-	-	Y	Y
State FE	-	-	-	Y

Table A21: **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^2	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^2	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 A22: **Drop multinational firms—alternative definition**

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 multinational firms, defined as those having at least one establishment abroad. "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		
Tariffs-hit×Post	0.0059***	0.0443***	0.6409***	0.5609***	0.3862***
	(0.0022)	(0.0079)	(0.0325)	(0.0386)	(0.0218)
Observations	672,096	792,947	113,780	113,780	117,496
R^2	0.7635	0.8135	-	-	-
			(B) By Bank Specialization		
Tariffs-hit×Post×Specialized Bank [1]	0.0011	0.0215	0.6781***	0.6124***	0.4161***
	(0.0034)	(0.0180)	(0.1540)	(0.1711)	(0.0959)
Tariffs-hit×Post×Other Bank [2]	0.0090**	0.0570***	0.6044***	0.5181***	0.3787***
	(0.0040)	(0.0177)	(0.1444)	(0.1555)	(0.0927)
Observations	672,096	792,947	93,291	93,291	97,449
R^2	0.7635	0.8135	-	-	-
p-value t-test Ha: $\|1\| > \|2\|$	-	-	0.039	0.087	0.121
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 A23: **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^2	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^2	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	-	-	-