Bank Financing of Global Supply Chains*

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Abstract

We study the relationship between financial frictions and trade dynamics by exploiting the reallocation of global supply chains induced by the 2018–2019 trade war. We match two administrative datasets—shipment-level import data with the U.S. credit register—to obtain comprehensive information on U.S. importer-supplier relations at the firm level and credit relationships at the bank-firm level. We show that firms importing products from China that were subject to tariffs during 2018–2019 increased their credit demand. Those firms increased credit line utilization and obtained more credit at higher spreads, especially from banks specialized in foreign input markets. Furthermore, firms borrowing from specialized banks or with multiple banking relationships were better able to find new suppliers and increase their import shares outside China than other firms. Our results highlight the importance of banking relationships for firms facing search costs related to trade disruptions and for supply chain resilience.

Keywords: supply chains, bank lending, tariffs, trade war, financial frictions, reallocation

JEL Codes: G21, F34, F42

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1 Introduction

In this paper, we examine the relationship between financial frictions and trade dynamics. In recent years, events such as the U.S.-China 2018–2019 trade war and Covid-19 pandemic have induced notable shifts in international trade patterns. In response to these shocks, some firms have started to relocate part of the production process and change the geographic footprint of their foreign sourcing of inputs. There is increasing evidence of shifting trade patterns and a "great reallocation" of global supply chains.[1] Yet, little is known about the factors that enable firms to find new customers and suppliers following these shocks. In this paper, we focus on the banking sector as an important force that may have shaped the adjustment of supply chains and trade patterns following the U.S.-China trade war.

To shed light on the role of bank financing in the realignment of supply chains around the trade war, we bring together, for the first time, two large-scale administrative datasets on trade relationships and bank credit for U.S. firms. We use the unanticipated introduction of trade tariffs in 2018–2019 by the United States on imports from China (Grossman, Helpman and Redding, 2023), and a difference-in-differences approach, to analyze changes in trade outcomes and bank credit for firms importing products subject to tariffs from China (henceforth, "tariffs-hit" firms).

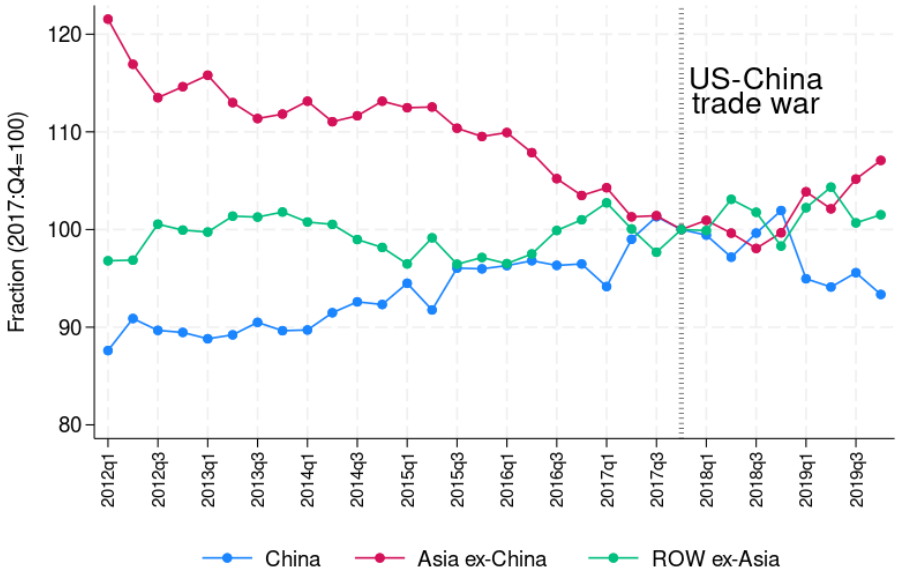
Our analysis documents a strong and robust relation between firms' access to bank credit and their ability to reconfigure supply chains: tariffs-hit firms obtain more bank credit in the period following the enactment of tariffs. In addition, those firms that have multiple banking relationships or borrow from banks with expertise in particular foreign markets and industries (i.e., "specialized banks") are more likely than other firms to adjust imports on both the extensive and intensive margins (import shares and entry/exit) as they establish supplier relationships in new markets. Our results emphasize the importance of banking relationships in boosting the resilience of supply chains to adverse shocks.

[1] See, among others, Aiyar, Presbitero and Ruta (2023); Alfaro and Chor (2023); Benguria and Saffie (2023); Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni (2023); Freund, Mattoo, Mulabdic and Ruta (2023).

Our paper uses a newly matched dataset for U.S. firms that combines information on import and export flows at the firm level, firms' borrowing activities from U.S. banks at the loan level, and key firm and bank balance sheet characteristics. We use transaction-level data from S&P Panjiva Global Market Intelligence (Panjiva in short) on U.S. firms' import volumes, values, and suppliers. Panjiva covers the universe of maritime trade shipments to the United States and spans the period from 2007 to date. The data have the advantage of providing firm identifiers, which enables us to track relationships between U.S. importing firms and their foreign suppliers across countries and over time. We combine these data with supervisory loan-level data from the Federal Reserve Y-14Q H1 Corporate Loan Data Schedule (informally known as the U.S. credit register and Y14 in short), which contains detailed information about individual loan contracts since 2012. The Y14 data report loan characteristics (including loan volumes, spreads, maturities, and collateral requirements) and credit line utilization on a quarterly frequency. The combined data allow us to examine the realignment of supply chains in response to the U.S.-China trade war at the firm level and the role of banking relationships in shaping this realignment at the loan level.

We start by documenting that firms that were importing at least one product from a Chinese supplier, most of which were affected by the 2018–2019 tariffs, reduced trade relationships with China and increased such relationship with suppliers elsewhere in Asia and the rest of the world (ROW). Figure 1 depicts the reduction in import shares from China and the increase in import shares from other countries in Asia and ROW during the trade war. In the empirical analysis, we establish these patterns using importer-supplier product-level data, which allow us to control for unobserved industry and location shocks to all firms. Our outcome variables are annual import shares (at the firm level) and the number of total, entering, and exiting suppliers from each region (at the firm-product level), which account for most of the cross-country variation in international trade flows. The effects of the 2018–2019 tariffs on the reconfiguration of supply chains that we document are robust to alternative measures of firm-level exposure to the trade war, including dummy

Figure 1: Reallocation of imports from China



Notes: The figure plots the share of imports for U.S. importers by region on a quarterly basis. Import shares are normalized to 100 in 2017:Q4. The figure is based on data from approximately 64 million shipments to 1.3 million importing firms that arrived in the United States during 2012:Q1-2019:Q4. Source: S&P Panjiva Supply Chain Intelligence.

variables that identify (a) firms importing products from Chinese suppliers that were subject to tariffs during 2018–2019 and (b) firms with significant Chinese imports (at least 10% of total imports). These results are consistent with recent studies that use aggregate data to document shifting trade patterns in the recent period (Alfaro and Chor, 2023; Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni, 2023; Freund, Mattoo, Mulabdic and Ruta, 2023).

Then, we analyze bank credit flows to firms that were importing tariff-hit products from China relative to other firms. We estimate loan-level regressions in the baseline period of two years before and after the trade war (2016:Q1–2019:Q4). We document that firms that imported tariff-hit products from China had higher corporate credit line utilization rates and were more likely to obtain new loans after the enactment of tariffs compared to other firms. Since corporate credit lines are precommitted lines of credit that can be tapped into

any time by borrowers with liquidity needs, higher credit line utilization is suggestive of higher credit demand. Furthermore, tariffs-hit firms obtained higher loan volumes at higher spreads, which is also suggestive of increased credit demand. Examining additional lending outcomes, we find that tariffs-hit firms received loans at shorter maturities and were more likely to post collateral against bank loans. These effects are robust to controlling for a wide range of firm characteristics (including size, leverage, cash holdings, profitability, and ex-ante risk), as well as state×time, industry×time, bank×time, and bank×firm fixed effects. Overall, these results suggest that those U.S. importers who were relatively more adversely impacted by the trade war increased their demand for credit, consistent with the implications of trade models with search costs (Grossman, Helpman and Redding, 2023).

Next, we analyze access to bank credit as a mechanism that may have shaped firms' input-sourcing decisions, and we show that tariffs-hit firms with stronger bank relationships obtain more credit. We use two measures of banking relationships. The first measure captures banking relationships through the lens of specialized banks with expertise in particular foreign markets and industries where their borrowers source their inputs. Bank specialization is defined following Paravisini, Rappoport and Schnabl (2023) as a high loan portfolio exposure to firms that source inputs from Asia (above the 75^{th} percentile). The second measure is a dummy taking value one for firms with multiple-banking relationships (representing about 11% of importing firms in the credit register) and zero for firms with a single banking relationship. Our analysis of lending outcomes shows that tariffs-hit firms borrowing from specialized banks obtain relatively more credit at higher spreads, suggesting that loan demand is bank-specific and increases for tariffs-hit firms during the trade war. Furthermore, those firms with multiple banking relationships receive higher loan volumes, but at relatively lower spreads compared to tariffs-hit firms with a single banking relationship. This result is consistent with the availability of multiple lenders being able to lower firms' financial frictions.

Lastly, we examine the role played by bank financing in U.S. importers' supply chain

reallocation from China to other markets during the trade war. For this purpose, we analyze within-firm changes in import shares and within-firm-product supplier entry/exit in the matched Panjiva–Y14 sample. We start by confirming that in this reduced sample of matched importers, the tariffs-hit firms reduced trade relationships with China and increased such relationships with suppliers elsewhere in Asia and ROW. Then, we test if the reallocation to Asia (excluding China) varies across two types of firms: firms in relationships with specialized banks or receiving loans from multiple banks (pre-trade war) versus other firms. We find that tariffs-hit firms with banks specialized in the Asian markets and firms with multiple banks were relatively better able to relocate their suppliers from China to other countries in Asia: such firms had a higher number of (new) suppliers and higher import shares from this market than other firms. The analysis suggests that banking relationships were critical for meeting the increased credit demand from firms seeking to relocate their sourcing of inputs on average, with stronger effects for those firms benefiting from specialized or multiple banking relationships.

Contribution to the literature This paper is related to several strands of literature. First, we contribute to the literature on the domestic and international impacts of the 2018-2019 trade war. Existing studies document the adverse effects of tariffs on U.S. real activity and consumer prices (Amiti, Redding and Weinstein, 2019; Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni, 2023; Flaaen, Hortaçsu and Tintelnot, 2020; Flaaen and Pierce, 2019), the U.S. financial sector (Correa, di Giovanni, Goldberg and Minoiu, 2023; Ozdagli, 2019), and global supply chains (Bown and Yilin, 2023; Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020; Grossman, Helpman and Redding, 2023; Qiu, Shin and Zhang, 2023).[2] Using aggregate trade data, Alfaro and Chor (2023), Freund, Mattoo, Mulabdic and Ruta (2023) and Goldberg and Reed (2023) show the "great realignment" of import sourcing from China towards other countries (primarily Vietnam and Mexico). At the firm level, exits from supplier relationships in response to tariff hikes were associated with lower export activity

[2]See Fajgelbaum and Khandelwal (2022) and Antràs and Chor (2022) for reviews.

for U.S. firms (Handley, Kamal and Monarch, 2024) and those firms with export exposure to China had lower profitability and worse stock market performance since the trade war began (Benguria, 2023; Huang, Lin, Liu and Tang, 2023). We expand this literature in two ways. First, we document the realignment of input sourcing by U.S. firms away from China and toward markets in Asia and ROW at the firm level, on both the intensive and extensive margins of imports. Second, we highlight the credit financing channel of this realignment and emphasize the role of bank specialization and relationships in firms' ability to reorganize their supply chains.

Second, our paper adds to the literature on the role of bank financing in facilitating international trade (Amiti and Weinstein, 2011; Manova, 2012; Michalski and Ors, 2012; Niepmann and Schmidt-Eisenlohr, 2017a,b) and firms' participation in global supply chains (Minetti, Murro, Rotondi and Zhu, 2019; Schiller, 2017). Many studies focus on the amplifying effects of banking sector shocks on trade-oriented firms (Alfaro, García-Santana and Moral-Benito, 2021; Chaney, 2016; Chor and Manova, 2012; Klein, Peek and Rosengren, 2002).[3] However, the role of banks as a potential absorbing force of real sector shocks has received less attention. In a related study, Benguria and Saffie (2023) document industry-level financial constraints in the reallocation of U.S. exports away from retaliating countries during the trade war. We contribute by supplying direct evidence on the impact of financial frictions, measured by the strength of banking relationships, on real activity. Furthermore, our results suggest a particular financial mechanism through which an increase in bank credit to firms facing supply chain disruptions facilitates the restructuring of their international trade activity.

Third, our paper relates to the literature on bank specialization and banking relationships. Banks that specialize in lending to firms in particular markets or sectors are more likely to experience increased loan demand when their borrowers are hit by adverse shocks (Paravisini, Rappoport and Schnabl, 2023) but also have the incentive to supply more loans

[3]See Foley and Manova (2015) for an overview of the literature.

to such borrowers to reduce the likelihood of defaults and balance sheet losses (Blickle, Parlatore and Saunders, 2023; Giannetti and Saidi, 2019). Lending relationships mitigate informational asymmetries between borrowers and lenders and are thus particularly valuable when information about a firm's potential investment opportunities is uncertain (Berger and Udell, 1995; Petersen and Rajan, 1994). Our results add to this literature by documenting the effects of banking relationships on the availability and cost of funds to firms engaged in international trade. Paravisini, Rappoport and Schnabl (2023) show that banks specialized in particular export markets experience 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 lenders. Our paper further emphasizes a supplier (as opposed to exporter) channel. In addition, our findings demonstrate that banking relationships are valuable not only in settings where informational asymmetries are large (as is the case for smaller opaque firms) but also for larger established firms such as those engaged in international trade.

2 The 2018–2019 Trade War

In 2018 and 2019, the U.S. enacted several waves of tariff increases targeting more than 13,000 10-digit HS product codes and over 100 trade partners.[4] A number of U.S. trade partners have retaliated by raising tariffs on U.S. exporters. In 2018 alone, the trade war is estimated to have resulted in 0.04% loss in the U.S. GDP (Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020), significantly raising consumer prices (Amiti, Redding and Weinstein, 2019) and reducing employment in the manufacturing sector (Flaaen and Pierce, 2019).

China has been at the forefront of the 2018-2019 trade war, with its imports to the U.S. valued at about $362 billion in 2017 being hit by tariffs varying between 10% and 25%. About 12,800 10-digit HS product codes, including solar panels, washing machines, textiles, steel,

[4] Bown and Kolb (2022) provides a detailed description of the timing of tariff increases and targeted countries.

and aluminum, have been hit by tariffs. Tariff hikes on Chinese imports were implemented in four waves: (i) 25% tariffs applied on $34 billion worth of products implemented in July 2018; (ii) 25% tariffs applied on $16 billion worth of products implemented in August 2018; (iii) 10% tariff applied on $200 billion worth of products implemented in September 2018, which was further raised to 25% in May 2019; (iv) 15% tariff applied on $112 billion worth of products implemented in September 2019 and then halved in February 2020. At the end of 2019, average U.S. tariffs on Chinese imports were six times higher than before the trade war.

3 Data

For the empirical analysis, we assemble a novel dataset on firm-level trade relationships and firm-bank lending relationships covering the period between 2012 and 2019. In short, the trade data cover the universe of shipments that arrived at U.S. ports and allow us to track firm-to-firm trade relationships for U.S. importers. The bank credit data cover close to three-quarters of credit commitments in the U.S. banking sector and provide detailed information for lending contracts of private and listed non-financial firms. Below, we discuss each dataset in detail and the process for merging the data for the analysis.

Firm-supplier Import Transaction Data We use transaction-level data from S&P Panjiva Global Market Intelligence on U.S. firms' import volumes, values, and suppliers. Panjiva Supply Chain Intelligence collects bill of lading (BoL) data from the U.S. Customs and Border Protection, which contain shipment-level 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, volumes in TEU (twenty-foot equivalent unit), and, in some cases, import values in USD.[5]

[5]S&P Panjiva Global Market Intelligence makes the bill of lading data available for imports and exports of 17 countries. We focus on the U.S. import sample, for which information on foreign suppliers (in particular, names and identifiers) that allow us to trace them in relation to U.S. importers are available.

Our sample covers the universe of maritime import flows to the United States between 2011Q1 and 2019Q4.

A unique advantage of the Panjiva data is the availability of importer and supplier identifiers. This allows us to track (firm-to-firm) relationships between U.S. importing firms and their foreign suppliers across countries and over time and examine the realignment of supply chains in response to the U.S.-China trade war *at the firm level*. Another key advantage of the data is the availability of the U.S. firm's name and address, which enables us to match the firms in Panjiva with the bank credit data (described further below).

Given that Panjiva data contain information on maritime shipments only, it is best suited for studying supply chain reallocation towards countries with which the U.S. trades by sea. For this reason, our analysis centers on supply chain relationships between U.S. importers and firms in Asia. Furthermore, we cannot assess the extent of supply chain reallocation towards Mexico and Canada, for which most trade occurs through airborne and land shipments. To address this data limitation, we exclude all products that U.S. firms predominantly import from Mexico and Canada. Despite its sole focus on maritime shipments, aggregated Panjiva data track the U.S. Census data closely during our sample period (see Figures 1 and A1).[6]

Bank-firm Loan-level Data ("U.S. Credit Register") To examine bank lending relationships, we use supervisory loan-level data from the FR Y-14Q H1 Corporate Loan Data Schedule. This dataset is part of the Dodd-Frank Y-14Q data collection effort and contains quarterly information on commercial and industrial (C&I) loans (with a size threshold of $1 million). The data are collected from the largest bank holding companies (BHCs) subject to stress tests (with at least $50 bn in total assets at end-2019). These data are often referred to as the "U.S. credit register" and cover between two thirds and three quarters of total U.S. C&I loans (Bidder, Krainer and Shapiro, 2021; Favara, Ivanov and Rezende, 2021).

The Y14 data provide comprehensive information about bank-firm lending relationships.

[6] Flaaen, Haberkorn, Lewis, Monken, Pierce, Rhodes and Yi (2023) provide a detailed overview of the Panjiva data.

Firms have unique identifiers that allow us to trace banking relationships over time and across banks. Each loan contract has a flag if it is a new loan origination and we observe if it is a corporate credit line or a term loan. For credit lines, we observe both the committed and utilized amount, which allows us to compute the credit line utilization rate (defined as the ratio between the total utilized amount and the total commitment). Furthermore, we have detailed information on the terms of lending for all outstanding loans: loan interest rates (set to zero for credit liens that are fully unutilized and dropped from the analysis), maturity, flags for secured loans, and collateral type.

For each borrower, the lenders report several balance sheet and income statement variables that we use as firm controls, 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 firms (mostly public firms). An advantage of the data is that we observe lenders' private assessments of each borrower's risk in the form of credit ratings in the S&P scale that are uniform across banks. Using the credit rating, we construct a dummy for high-yield firms (taking value one for those firms with an S&P rating of BB or below). We use this variable as a measure of ex-ante borrower risk and a critical control variable in the bank lending regressions. In the main analysis of loan contracts, all firm variables are measured at end-2017 and are thus predetermined relative to the start of the trade war. In the analysis of trade outcomes, firm variables are measured at end-2017 for those firms with available data, or end-2016 for other firms.

Matching the S&P Panjiva Global Market Intelligence and Y14 Datasets The two datasets do not share any common identifiers. Therefore, we conduct a string match on the firm name to link the firms across the two datasets, as follows. We carefully clean and uniformize the firm names in the two datasets: we start with approximately 1.5 million U.S. importers during 2010–2019 and about 310 thousand borrowing firms in the Y14 dataset with outstanding loans during 2012—2021. Then, we proceed in two steps to obtain an

accurate match. In the first step, we conduct an exact match on firm name, which results in 48,476 matches. In the second step, we bring additional information to find an Y14 match for the unmatched importers. Specifically, we identify their ultimate corporate parent using the identifier crosswalks from S&P BECRS (Cross Reference Services Business Entity Linking) dataset. That is, we match each Panjiva ID firm to the Capital IQ identifier (CIQ) in BECRS and obtain the ultimate parent from Capital IQ. We clean and uniformize the names once again and repeat the exact matching procedure on firm names. The total number of matched importing firms is 68,345 firms, which are linked to 56,786 borrowing firms (including parent firms) in the credit register. Of these borrowing firms, we have balance sheet information at end-2017 for 12,500 firms. This number of firms is smaller than that of matched firms because balance sheet data are only available when reported by at least one lender, and thus, the firm has outstanding loan balances with that lender.

Tariff Data We use data on tariffs imposed by the U.S. on its trading partners in 2018 and 2019 from Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020) and Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni (2023). These data identify 10-digit HS products and countries targeted by the 2018-2019 tariffs and document the month of the tariff change and the applied rate.

4 Results

4.1 Tariffs and supply chain reconfiguration

Specification. We first evaluate the extent of supplier switching by U.S. firms in response to the increase in import tariffs imposed by the U.S. on China in 2018 and 2019. For each product p imported by the U.S. firm i, we compute the total number of suppliers total_{ipt}^{j} in year t in one of three distinct markets denoted by j: China, Asia excluding China, and the

rest of the world (ROW) excluding Asia.[7] We then compare the composition of suppliers in a year t with the previous year $t-1$ and identify entering and exiting suppliers. entry^j_{ipt} is defined as a number of firm i's suppliers of product p that are absent from the set of suppliers located in region j in year $t-1$ but are present in year t. Conversely, exit^j_{ipt} is a number of firm i's suppliers of product p in region j that are present in year $t-1$ and absent in year t. In addition, we construct import volume shares (in TEU) of region j for each firm i in year t and denote it by impshare^j_{it}.

We adopt a difference-in-differences (DiD) approach to assess the effect of the U.S.-China trade war on suppliers switching away from China and towards other Asian countries and ROW. In our baseline specification, we define a firm and product combination as treated if the firm imported at least one product from a Chinese supplier during 2016-2017 (before the onset of the trade war) and a given product was hit by a higher tariff on China during the 2018-2019 trade war. The estimating equation for the baseline regression is:

$$Y^j_{ipt} = \alpha^j + \beta^j \text{Tariff-hit}_{ipt} \times \text{Post}_t + \sigma^j_{ip} + \theta^j_{pt} + \phi^j_{kt} + \delta^j_{st} + \epsilon^j_{ipt}, \tag{1}$$

which we estimate for each market j separately (China, Asia excluding China, and ROW excluding Asia). Y^j_{ipt} denotes the total number of suppliers, exits, or entries for market j, firm i, product p (6-digit HS code), and year t. Alternatively, for import shares as a dependent variable, we use product-time variation only for a given market j. The specification includes firm×product fixed effects (σ_{ip}), product×year fixed effects (θ^j_{pt}), state×year fixed effects (δ_{st}), and 3-digit NAICS industry×year fixed effects (ϕ^j_{kt}). We estimate Equation 1 using Poisson Pseudo Maximum Likelihood (PPML) estimator, which is suitable for count models with a large share of zero values in the dependent variable.

[7] We are following the definition of countries in Asia and the Pacific from the IMF's World Economic Outlook.

Results. We present the estimates for all firms in Panjiva data in Table 1 as well as a subset of these firms matched with the Y14 in Table 2.[8] In both samples of firms, we see strong reallocation effects away from China and towards suppliers in other Asian countries and in the ROW. While the number of suppliers in China (Asia and ROW) declines (increases), the number of existing suppliers increases (declines). Thus, we see that firms affected by tariffs imposed on Chinese imports respond by terminating their relationships with Chinese suppliers and entering new relationships with suppliers located elsewhere. In addition, these firms are less likely to form new relationships with Chinese suppliers and more likely to continue existing relationships with suppliers in Asia and ROW. As a result, the import share from Chinese suppliers declines (Column 1), and the overall number of Chinese suppliers declines (Column 2). The decline in the number and import share of Chinese suppliers is offset by the rising number of suppliers and total import share of Asia (ex. China) and the ROW. The magnitude of the effects is comparable for the entire sample of firms in Panjiva data and Y14-matched firms, with an even stronger effect on exits from relationships with Chinese suppliers but a more muted increase in Asian import share. Overall, these results corroborate the evidence on aggregate reallocation patterns documented in Alfaro and Chor (2023), Freund, Mattoo, Mulabdic and Ruta (2023), and Goldberg and Reed (2023).

Tables 3-5 show results for Y14-matched firms with alternative definitions of the treatment variable. In Table 3, we allow for staggered treatment, i.e., some firms import products that get hit by the last wave of tariffs in 2019. In Table 4, we define firms as treated if they were ex-ante exposed to China, i.e., if a firm imported at least one product from China in 2016 and/or 2017. In Table 5, we consider a firm as treated if, on average, at least 10% of its imports originated from China in 2016 and 2017. Overall, these results are consistent with our baseline (Table 2). Interestingly, our results for staggered treatment specification in the Panel A of Table 3 are smaller for Chinese suppliers compared to Table 2, which could suggest strong anticipatory effects on the side of yet-to-be-treated firms in 2018. In

[8]The full sample consists of all Y14-matched firms and a 10% random sample of unmatched firms.

other words, when yet-to-be-treated firms are included in the control group in the staggered specification, the estimated treatment effect may be lower due to yet-to-be-treated firms' pausing entrance into new relationships with Chinese suppliers and ending existing ones in anticipation. However, given that the magnitudes of the effects for suppliers in Asia (ex. China) and ROW are largely unchanged, yet-to-be-treated firms appear to enter these locations later. These effects are consistent with the fact that tariff hikes were announced well in advance of the date that they went into effect giving firms a head start in the adjustment process.

5 Conclusions

TO BE ADDED

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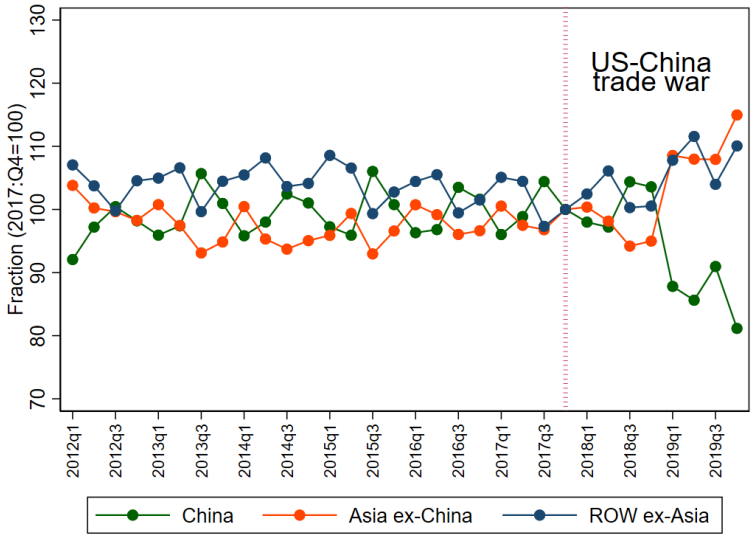
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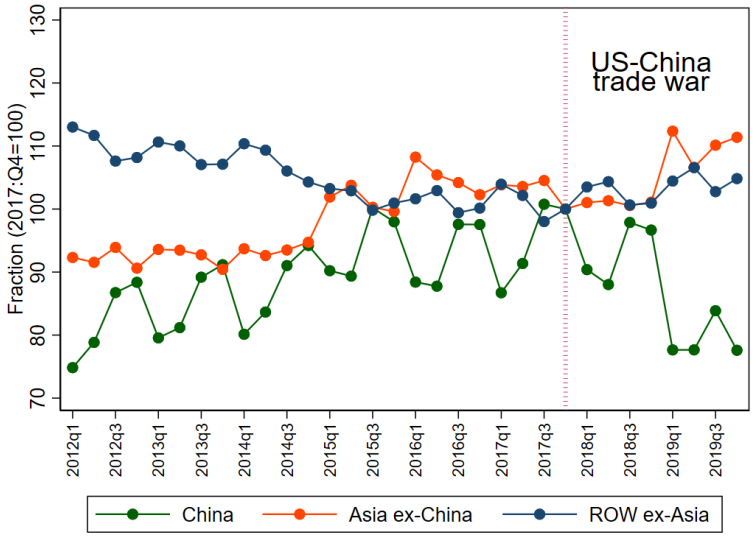
A Figures and Tables

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

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



(a) Maritime imports



(b) Total imports

Table 1: **Trade war effect on supply chain realignment: All firms**

This table reports PPML estimates from a regression of trade outcomes on China tariff-hit dummy variable interacted with Post as shown in Equation 1. The dependent variables are the import volume share or the number of suppliers (total, exiting, and entering). The sample includes all importing firms in Panjiva data. Panel A refers to suppliers located in China, Panel B refers to suppliers in Asia and the Pacific excluding China, and Panel C refers to suppliers in ROW excluding Asia and the Pacific. In Column 1 the data are at the firm-year level; in columns 2–4 the data are at the firm-product-year-level (6-digit HS codes). The sample period is 2011:Q1–2019:Q4. China-tariff-hit dummy variable takes value one for firms that imported during 2016–2017 from a Chinese supplier at least one product subject to tariffs at either point in time during 2018 or 2019. Standard errors are clustered on firm (Column 1) or firm-product (Columns 2–4). *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
	import share	**total # suppliers**	**# exiting suppliers**	**# entering suppliers**
			(A) China	
China-tariff-hit × Post-2018	-0.586***	-0.665***	1.387***	-1.173***
	(0.011)	(0.019)	(0.025)	(0.021)
Observations	585790	1756966	1707903	1719620
			(B) Asia excl. China	
China-tariff-hit × Post-2018	0.162***	0.340***	-0.572***	0.638***
	(0.007)	(0.007)	(0.009)	(0.010)
Observations	543727	1688216	1629614	1631191
			(C) ROW excl. Asia	
China-tariff-hit × Post-2018	0.202***	0.305***	-0.494***	0.533***
	(0.008)	(0.015)	(0.016)	(0.018)
Observations	483509	1287439	1243117	1253772
Firm FE	✓			
Firm×product FE		✓	✓	✓
Product×year FE		✓	✓	✓
State×year FE	✓	✓	✓	✓
Industry×year FE	✓	✓	✓	✓

Table 2: **Trade war effect on supply chain realignment: Credit-register matched firms**

This table reports PPML estimates from a regression of trade outcomes on China tariff-hit dummy variable interacted with Post as shown in Equation 1. The only difference from Table 1 is that the sample comprises only the firms matched to the credit register. Standard errors are clustered at the firm level (Column 1) or firm-product level (Columns 2–4). *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
	import share	**total # suppliers**	**# exiting suppliers**	**# entering suppliers**
			(A) China	
China-tariff-hit × Post-2018	-0.460***	-0.564***	1.494***	-1.118***
	(0.029)	(0.046)	(0.056)	(0.048)
Observations	141579	820474	789961	796470
			(B) Asia excl. China	
China-tariff-hit × Post-2018	0.068***	0.289***	-0.510***	0.588***
	(0.014)	(0.011)	(0.014)	(0.015)
Observations	140903	782472	748561	748245
			(C) ROW excl. Asia	
China-tariff-hit × Post-2018	0.081***	0.230***	-0.428***	0.420***
	(0.013)	(0.019)	(0.023)	(0.024)
Observations	143699	573738	546983	552705
Firm FE	✓			
Firm×product FE		✓	✓	✓
Product×year FE		✓	✓	✓
State×year FE	✓	✓	✓	✓
Industry×year FE	✓	✓	✓	✓

Table 3: **Trade war effect on supply chain realignment: Staggered treatment**

This table reports PPML estimates from a regression of trade outcomes on China tariff-hit dummy variable interacted with Post as shown in Equation 1. The only difference from Table 2 is that the diff-in-diff term "China-tariff-hit × Post" is staggered, i.e. is a dummy that takes value one in the year when the firms get hit by tariffs (2018 or 2019). Standard errors are clustered at the firm level (Column 1) or firm-product level (Columns 2–4). *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
	import share	**total # suppliers**	**# exiting suppliers**	**# entering suppliers**
			(A) China	
China-tariff-hit × Post	-0.366***	-0.339***	0.779***	-0.683***
	(0.027)	(0.041)	(0.047)	(0.046)
Observations	141579	820474	789961	796470
			(B) Asia excl. China	
China-tariff-hit × Post	0.070***	0.290***	-0.513***	0.609***
	(0.014)	(0.011)	(0.015)	(0.017)
Observations	140903	782472	748561	748245
			(C) ROW excl. Asia	
China-tariff-hit × Post	0.082***	0.231***	-0.428***	0.430***
	(0.013)	(0.019)	(0.024)	(0.025)
Observations	143699	573738	546983	552705
Firm FE	✓			
Firm×product FE		✓	✓	✓
Product×year FE		✓	✓	✓
State×year FE	✓	✓	✓	✓
Industry×year FE	✓	✓	✓	✓

Table 4: **Trade war effect on supply chain realignment: Ex-ante exposure to Chinese suppliers**

This table reports PPML estimates from a regression of trade outcomes on China tariff-hit dummy variable interacted with Post as shown in Equation 1. The only difference from Table 2 is that the treatment variable is "Exposed to China", a dummy that takes value value one for firms that imported at least one product from China during 2016–2017. Standard errors are clustered at the firm level (Column 1) or firm-product level (Columns 2–4). *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
	import share	**total # suppliers**	**# exiting suppliers**	**# entering suppliers**
			(A) China	
Exposed to China × Post-2018	-0.525***	-0.564***	1.477***	-1.120***
	(0.029)	(0.043)	(0.053)	(0.046)
Observations	141579	820474	789961	796470
			(B) Asia excl. China	
Exposed to China × Post-2018	0.068***	0.098***	-0.130***	0.213***
	(0.014)	(0.015)	(0.020)	(0.021)
Observations	140903	782472	748561	748245
			(C) ROW excl. Asia	
Exposed to China × Post-2018	0.082***	0.107***	-0.185***	0.208***
	(0.013)	(0.015)	(0.018)	(0.019)
Observations	143699	573738	546983	552705
Firm FE	✓			
Firm×product FE		✓	✓	✓
Product×year FE		✓	✓	✓
State×year FE	✓	✓	✓	✓
Industry×Year FE	✓	✓	✓	✓

Table 5: **Trade war effect on supply chain realignment: Ex-ante Chinese import share $> 10\%$**

This table reports PPML estimates from a regression of trade outcomes on China tariff-hit dummy variable interacted with Post as shown in Equation 1. The only difference from Table 2 is that the treatment variable takes value value one for firms whose import share from China was at least 10% of total import volumes during 2016–2017. Standard errors are clustered at the firm level (Column 1) or firm-product level (Columns 2–4). *** 1%, **5%, *10%.

	(1)	(2)	(3)	(4)
	import share	**total # suppliers**	**# exiting suppliers**	**# entering suppliers**
			(A) China	
China import share $> 10\% \times$ Post	-0.478***	-0.301***	0.330***	-0.555***
	(0.025)	(0.021)	(0.024)	(0.025)
Observations	141579	820474	789961	796470
			(B) Asia excl. China	
China import share $> 10\% \times$ Post	0.050***	0.004	-0.167***	0.107***
	(0.013)	(0.011)	(0.014)	(0.016)
Observations	140903	782472	748561	748245
			(C) ROW excl. Asia	
China import share $> 10\% \times$ Post	0.071***	-0.011	-0.182***	0.086***
	(0.016)	(0.016)	(0.017)	(0.019)
Observations	143699	573738	546983	552705
Firm FE	✓			
Firm×product FE		✓	✓	✓
Product×year FE		✓	✓	✓
State×year FE	✓	✓	✓	✓
Industry×Year FE	✓	✓	✓	✓