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SUPPLY CHAIN ADJUSTMENTS TO TARIFF SHOCKS: EVIDENCE FROM FIRM TRADE LINKAGES IN THE 2018-2019 U.S. TRADE WAR

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ABSTRACT

We use the 2018-2019 U.S. trade war to examine how supply chains adjustments to a tariff cost shock affect imports and exports. Using confidential firm-trade linked data, we show that the decline in imports of tariffed goods was driven by discontinuations of U.S. buyer–foreign supplier relationships, reduced formation of new relationships, and exits by U.S. firms from import markets altogether. However, tariffed products where imports were concentrated in fewer suppliers had a smaller decline in import growth. We then construct measures of export exposure to import tariffs by linking tariffs paid by importing firms to their exported products. We find that the most exposed products had lower exports in 2018-2019, with most of the impact occurring in 2019.

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1 Introduction

Global supply chains are a pervasive feature of the modern production landscape (Hummels, Ishii and Yi, 2001; Johnson and Noguera, 2017) and a potentially important channel of transmitting shocks through an economy. This paper uses detailed U.S. firm-level data to measure two dimensions of firm linkages in supply chains: (1) the relationships *between* U.S. buyers and foreign suppliers of imports, and; (2) the *within* firm linkages from imported inputs to exported output at importer-exporter firms. We show the role of these linkages in U.S. firms adjustments of imports and exports in response to the U.S. trade war from 2018 to 2019, in which, by August of 2019, \$290 billion of U.S. imports - about 12% of the total - were subject to an average tariff increase of 24 percentage points.[1]

One key consideration for how firms may adjust their global supply chain is whether there are (or are not) many other options for sourcing products. The vulnerability of an imported product to trade shocks such as tariffs depends on the availability of alternative suppliers. We thus begin our analysis by using two-sided U.S. trade transaction data to generate a measure of foreign supplier concentration at a detailed product level. This measure captures how U.S. imports of a product are spread across foreign suppliers: products that are sourced from a few suppliers are especially vulnerable to shocks hitting those suppliers. We show that for "strategic" products like rare earths, chemicals, and pharmaceuticals, the vulnerability of U.S. imports to the tariff shock is higher than would be suggested from aggregate U.S. import data.

We then consider the effects of the 2018–2019 U.S. trade war on imports coming from adjustments to U.S. firms' supply chains. It is well-known that U.S. imports of tariffed products dropped substantially in response to the tariffs (Amiti, Redding and Weinstein, 2019; Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020). Our contribution is to investigate whether the decline in imports following the tariffs occurred within continuing buyer-supplier relationships or instead, came from the ending of such relationships. This distinction matters for supply chains when there are fixed costs of restarting or establishing new relationships. If trade relationships are broken, imports may not recover quickly even if many alternative suppliers are available. Each new tariff potentially disrupts at least one, and possibly many more trade relationships between foreign suppliers and U.S. buyers. Moreover, the concentration of products across foreign suppliers could directly shape the nature of the disruption.

[1] Calculated on an annual basis using 2017 data.

We find the import decline in products facing tariffs accrues primarily to the *extensive margin*: relationships ending, fewer relationships forming, and U.S. firms exiting from sourcing in foreign markets. However, affected products with imports concentrated in fewer suppliers had a *smaller* decline in growth rates, as the negative contribution from the exit of importers is much weaker. In other words, in response to import tariffs, concentrated products are less responsive at the extensive margin, i.e. there are fewer importers exiting or foregoing entry. This suggests that such products are more difficult to start or stop buying, and there are fewer short-term alternatives available to re-optimize the supply chain after the cost shock.

We next turn to studying the effects of the 2018–2019 U.S. trade war on exports stemming from adjustments to U.S. firms' supply chains. Our main emphasis here is on the importance of data on the *import-export* linkages within firms for understanding the effects of supply chain adjustments. This is because the new trade war import tariffs in 2018-2019 were cost shocks on a variety of imported inputs for the output that firms were exporting. Simultaneously, many of these same firms were also facing negative demand shocks from retaliatory tariffs on their exports. Importantly, U.S. export growth was notably weak from mid-2018 through late 2019, a weakness that extended beyond the major products and countries that were targeted by new tariffs (Handley, Kamal and Monarch, 2020).

Our goal is to measure the propagation of the tariff shock into U.S. exports by examining which exported products rely heavily on newly tariffed imports. To do this, we generate links from imports to exports for the U.S. firms that both import and export in the same year. This leverages the empirical regularity that most U.S. merchandise trade is mediated by firms that both import and export and their trading status is persistent over time (Bernard, Jensen, Redding and Schott, 2018).[2] By identifying the exporters in a pre-tariff period that imported products on which tariffs were imposed in 2018-2019, we construct measures of import tariff exposure for exported products: products where more exports came from firms with a heavier tariff burden are more exposed to the tariffs. Combined with official monthly public-use export data from 2015 through 2019, we measure the impacts of exposure to increases in import tariffs on U.S. exports.

We find that supply chain spillovers from increased import tariffs dampened U.S. exports over 2018-2019 for the typical affected export product, even after controlling for foreign-imposed retaliatory export tariffs. Our estimates imply that exports were 2.9 log points lower on average by 2019 from exposure to U.S. import tariffs. This accounts for over half

[2]The top 1 percent of traders account for over 80 percent of total U.S. goods trade (Bernard, Jensen, Redding and Schott, 2018).

of the otherwise unexplained weakness we find in U.S. exports in 2019 relative to the pre-trade war period from 2015-2017. By 2019, the resulting supply chain production frictions for exporters were equivalent to an *ad valorem* tariff of about 2% on U.S. exports at mean exposure and up to 4% or more for products with high exposure.

Our objective is to broaden our understanding of the impact of the 2018-2019 tariff wars in an era of outsourcing and global production networks. Our contribution is thus complementary to several recent papers that study the trade effects of the 2018-2019 tariffs. Amiti, Redding and Weinstein (2019) and Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020) study the direct impacts of the 2018-2019 U.S. import tariff increases on U.S. import prices and import values as well as the direct impact of the foreign retaliatory tariff increases on U.S. export prices. Both papers find large declines in U.S. imports. Cavallo, Gopinath, Neiman and Tang (2021) also examine the pass-through of U.S. import tariff increases to U.S. importers and retailers using firm-level data. However, these studies do not consider spillover effects of increases in U.S. import tariffs on U.S. exports through supply chains. An exception is Benguria and Saffie (2019), but they rely on aggregated input-output tables to study the impact of tariffs and uncertainty on U.S. exports.[3]

2 Supply Chain Vulnerabilities to Trade Shocks

Our first exercise is to use information on foreign exports to the United States to measure the concentration of U.S. imports across foreign suppliers. This is important to understanding how firms adjusted their supply chains to the 2018–2019 tariffs and can reveal how feasible substitution to alternate suppliers may be in practice. We emphasize the importance of considering product-level dimensions of concentration that rely on supplier-level data, and reveal the extent to which aggregate data masks the degree of vulnerability that U.S. importers confront.

We rely on Longitudinal Firm Trade Transactions Database or LFTTD (Kamal and Ouyang, 2020) for our analysis. The LFTTD contains the universe of merchandise import

[3]Several papers examine non-trade outcomes. Waugh (2019) studies the impact of Chinese retaliatory tariffs in 2018 on U.S. consumption to find that counties more exposed to Chinese tariffs experienced 2.5 percentage points lower growth in auto sales compared to counties with lower exposure. Blanchard, Bown and Chor (2019) study the impact of a county's exposure to U.S.-imposed import tariffs and foreign retaliatory export tariffs on the county's Republican vote share in the 2018 U.S. House elections. Flaaen and Pierce (2019), using aggregated input-output tables, examine the effect of higher input costs from the 2018-2019 U.S. import tariffs on domestic output and employment in the U.S. manufacturing sector; Bown, Conconi, Erbahar and Trimarchi (2020) carry out a similar analysis but consider the supply chain effects of anti-dumping duties.

transactions valued at or over $2,000. The LFTTD uniquely identifies the U.S. firm and the foreign supplier in an import transaction. Foreign supplier information appears in the manufacturer identifier (MID) which is an alphanumeric code constructed using a combination of the name and address of the foreign manufacturer (Kamal and Monarch, 2018). Using the MID, we measured a U.S. firm's purchased imports at the country-product-supplier level.

With the LFTTD, we can create a measure of "foreign concentration" for U.S. imports as a way to measure how easy it may be to find alternative import sources in response to shocks. The measure is a Hirschman-Herfindahl Index (HHI) defined for an imported HS6 product p (HHI_p) as follows,

$$HHI_p = \sum_s \left[\frac{M_{sp}}{\sum_s M_{sp}} \right]^2 \tag{1}$$

where M_{sp} is the import value of HS6 product p from source s. The granularity of s could be a source country or supplier firm depending on the available data. The HHI_p is the sum of squared import shares, with a lower value reflecting that imports are more evenly dispersed across sources.[4] For any product p, the measure can be calculated (using publicly available trade data) defining sources at the country level. We construct this measure and label it HHI_p^C, where superscript C denotes it is measured by source country.

Using the two-sided firm-to-firm trade transaction data available in the LFTTD, we can also generate a "supplier-based" HHI_p, where sources are instead defined as individual suppliers selling products to U.S. importers. We use superscript S to denote these supplier and denote the measure by HHI_p^S. The distinction between these two measures is important for assessing the vulnerability of particular sectors to shocks. For example, it is possible that imports of a certain product may be exclusively coming from one country, which would give a country-based HHI_p^C equal to 1. However, if there are many suppliers being used in that country, then the shocks to which imports are vulnerable are of a different nature than if there are few suppliers in that country. Similarly, if imports are spread across many countries, giving a low HHI_p^C, but there are few suppliers in each country, then the aggregate data could mask the true vulnerability of that product to local shocks.

To demonstrate the implications that can emerge from this distinction, we consider two different types of shocks. The first type of shock is one that is <u>localized</u> and is a function of the supplier decisions for individual U.S. importers. Disruptions to a supplier may

[4] For example, if a product is imported from 10 sources, each supplying 10% of imports, the HHI_p would be 0.10. However, a product with 10 sources where one source supplies 91% of the imports and the other 9 supply 1% each would result in an HHI_p of 0.83.

cause larger economic effects if imports are concentrated in a small number of suppliers. A major supplier experiencing financial trouble when there are few alternatives, geographically-contained factory shutdowns, shipping delays from individual producers, or targeted, supplier firm-specific anti-dumping/countervailing duties; these are all examples of shocks that are supplier-based in nature. For vulnerability to this type of shock, the supplier-based HHI_p^S is more relevant.

An alternative type of shock is a source-wide shock in which the key change is one that is affecting all suppliers within a source country. Increases in applied tariffs, shipping delays due to country-specific policies, or geopolitical trade sanctions or conflicts are all examples of source-wide shocks. The HHI_p^C measure can capture vulnerabilities due to these country-specific shocks.

To illustrate how these measures might differ, we consider imported products that were identified by the Biden Administration's "Supply Chain Disruptions Task Force" as having particular national security importance (The White House, 2021). We identify the following groups of HS-6 products in the LFTTD: batteries, semiconductors (considered to be "machinery"), rare earths (considered to be "chemicals"), and pharmaceuticals.

The vulnerability of these imported products to different types of shocks based on 2017 import data is shown in Table 1. The table shows that the average supplier-level HHI_p^S across all imported products is 0.18. Rare earths, chemicals, and pharmaceuticals tend to be have higher concentration than average; semiconductors and batteries exhibit lower concentration than average. Rare earths, chemicals, and pharmaceuticals also have far fewer suppliers than average. In 2017, there were only 56 individual suppliers of rare earths, in contrast to over 2,000 for semiconductors. Thus, some products identified as strategic imports by the Biden Administration have few alternative suppliers and are thus more at risk from localized shocks compared to other imported products such as apparel and textiles.

The right panel of Table 1 shows the same products but examines the concentration at the country rather than supplier-firm level. These measures are clearly different from those in the supplier-level data. Very few products diverge meaningfully from average in terms of the country-based HHI_p^C. In other words, although rare earths, chemicals, and pharmaceuticals do not appear particularly concentrated in particular source countries, the supplier-level data reveals that there are a large amount of imports in a small number of suppliers. Semiconductors are also a very interesting example: although they have been identified as a product of key strategic importance, imports of semiconductors are spread evenly across 59 different source countries. However, the HHI_p^S measure is much closer to the average, indicating that there are relatively few suppliers of semiconductors, even though they are spread across many source countries.

In sum, our measures reveal pronounced foreign supplier concentration in rare earths, chemicals and pharmaceuticals. This picture emerges only by considering the supplier-based measures of concentration. Thus we conclude that country-based concentration shares need not be particularly good proxies for measuring the degree of supplier concentration and thus are less informative about the effects of localized shocks.[5]

3 Decomposing the Import Response to Tariffs

In this section we focus on understanding changes in imports in response to the import tariff hikes during the 2018–2019 trade war using the LFTTD. The tariff hikes were widespread: over 10,000 HS-country pairs, more than half coming from China, faced import tariff increases.[6] There were three broad tariff tranches: (1) solar panels and washing machines (January 2018), (2) metals (spring 2018), and (3) tariffs on Chinese products (summer 2018 through May 2019). The tariff increases fell mainly on intermediate goods (57% of the total value of goods receiving tariffs) compared to 27% for capital and 16% for consumption goods.[7] Existing work has shown definitively that U.S. imports of affected products dropped substantially (Amiti, Redding and Weinstein, 2019; Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020).

For studying how firm-level supply chain adjustments affected U.S. imports, the linkage we focus on is that between a U.S. buyer and its foreign supplier. Using firm-transactions linked data from the 2018–2019 period, our results center on firm-level responses to import tariffs using country and product level import growth measures that parsimoniously capture the intensive and extensive margins of supplier-specific sourcing. We are especially interested in whether the fall in U.S. imports occurred *within* existing buyer-supplier relationships, or instead arose due to reduced trade participation at either the relationship level or the firm level. In particular, we quantify the importance of U.S. importer-foreign exporter relationship dissolution for explaining the large declines in U.S. imports that accompanied the import

[5] Additional data points that could be used to compare localized shocks to country-specific shocks, including the share of U.S. imports in these products coming from "friendly" countries, can be found in Appendix A. We also include sourcing details on medical products that were in high demand during the early pandemic period in Appendix A.

[6] We match the new tariff lines, at the HS 8-digit level, by date in 2018-2019 sourced from the U.S. International Trade Commission, to country-product level annual import totals in 2016; details in Appendix B.

[7] Calculated using the United Nation's Broad Economic Classification to classify goods in 2017 annual import data.

tariffs, and relate changes in those buyer-supplier margins to product-level concentration of trade among suppliers.

3.1 Methodology

We define imports M_{cpt} by source country (c), HS6 product (p), and year (t) and compute the growth rate as $g_{cpt} = \frac{M_{cpt} - M_{cp,t-1}}{\overline{M}_{cpt,t-1}}$, which is the difference in trade normalized by average trade $\overline{M}_{cpt,t-1} = (M_{cpt} + M_{cp,t-1})/2$ between two periods.[8] This trade growth measure can be decomposed into the contributions from the intensive margin (continuing relationships that are expanding or contracting) and the extensive margin (adding/dropping of suppliers within source countries or the entry and exit from foreign sourcing).

Through the lens of two-sided relationship data, there are three avenues through which the total value of trade may be increasing from time $t-1$ to t.

1. An expansion of trade in continuing buyer(b)-supplier(s) relationships. We define this "trade creation" as $TC_{cpt} = \sum_{bs \in cont} \max\{M_{bscpt} - M_{bscp,t-1}, 0\}$, where M_{bscpt} represents buyer b's imports from supplier s located in country c of product p at time t and $cont$ is the set of continuing relationships from $t-1$ to t. Thus TC^{cont}_{cpt} captures the positive change in imports from growing relationships.

2. Imports from newly formed buyer-supplier relationships in country c by buyers already importing from c. We define these imports as $ADD_{cpt} = \sum_{bs \in ADD} M_{bscpt}$, where the set of new relationships ADD consists of new buyer-supplier links but conditions on b having imported from c at time $t-1$.

3. Imports from newly formed buyer-supplier relationships in country c where the buyers are also newly importing from c. We define these imports as $ENTRY_{cpt} = \sum_{bs \in ENTRY} M_{bscpt}$, where the set of new relationships $ENTRY$ also consists of new buyer-supplier links but conditions on b not importing from c at time $t-1$.

These three measures are mirrored for cases where trade is declining.

1. Import declines in continuing buyer(b)-supplier(s) relationships is defined as "trade destruction" $TD_{cpt} = \sum_{bs \in cont} \min\{M_{bscpt} - M_{bscp,t-1}, 0\}$

2. Imports "lost" from the discontinuation of existing buyer-supplier relationships in country c by continuing buyers (b) are given by $DROP_{cp,t-1} = \sum_{bs \in DROP} M_{bsp,t-1}$

[8] This rate is symmetric, bounded on $[-2, 2]$, and accommodates zeroes. It is equivalent to log changes up to a 2nd-order Taylor approximation and has been used in dynamic trade analysis (e.g. Carballo et al. (2022)).

3. Imports "lost" from the exit of buyers from all existing relationships in country c is $EXIT_{cp,t-1} = \sum_{bs \in EXIT} M_{bsp,t-1}$.

Adding the three trade creation measures and subtracting the three trade destruction measures recovers the aggregate change in trade $M_{cpt} - M_{cp,t-1}$ for imports in a particular source-product. This means that we can decompose import growth across the margins defined above as:

$$g_{cpt} = \frac{TC^{cont}_{cpt} - TD^{cont}_{cpt} + ADD_{cpt} - DROP_{cp,t-1} + ENTRY_{cpt} - EXIT_{cp,t-1}}{(M_{cpt} + M_{cp,t-1})/2}. \tag{2}$$

This growth decomposition illuminates the contribution of each margin to changes in U.S. imports that are masked in aggregated data. For example, import growth in a particular country-product may be stable and consistent, but the ADD_{cpt} and $DROP_{cp,t-1}$ measures could indicate substantial churning in buyer-supplier relationships, which suggests firms are easily substituting across suppliers. Alternatively, if imports from c decline in response to new tariffs, the decomposition would reveal whether the decline was from a contraction within existing relationships (TD), buyers dropping suppliers within c ($DROP$), a slowdown in trade within existing relationships (TC), or the exit of buyers from the source country ($EXIT$). The first two terms in the numerator of Equation 2 would be capturing intensive margin effects (with their difference equal to "net trade creation" within relationships) while the latter four terms would all be extensive margin effects.

3.2 Results

Table 2 shows the result of these decompositions for U.S. import growth from 1993 through 2019. Average U.S. import growth was 6.6% over these years. Import growth related to the extensive margin—the combination of ($ADD_{cpt} - DROP_{cp,t-1}$) and ($ENTRY_{cpt} - EXIT_{cp,t-1}$)—accounts for about 60% of overall import growth; the remaining 40% is net trade creation within existing relationships given by ($TC_{cpt} - TD_{cpt}$).

The contribution of the extensive margin illustrates the importance of relationship churning for U.S. imports. Trade growth due to the two components of the extensive margin—the adding/dropping of existing relationships and the net entry of U.S. importers—was almost equal over this time period. Figure 1 shows that within-relationship trade flows are important for explaining the overall trend in import growth from 1993–2019: the intensive margin measure of within-relationship trade changes matches the path of overall import growth very well over the time series.[9]

We next estimate the effect on supply chain relationships of the 2018–2019 U.S. tariffs. Our identification strategy is to use country and time variation from the U.S. trade war to estimate the effects on buyer-supplier import growth margins. Although it is now well known that the trade war had a negative impact on import volumes (cf. Amiti et al., 2019), we mainly have only anecdotal evidence on whether import reductions occurred on the intensive margin of existing trade relationships or the extensive margin. This distinction is important because forming buyer-supplier relationships in a supply chain can require sunk bilateral investments, which makes the decision to start or stop a trading relationship complex. Sunk relationship costs may make buyers and suppliers reluctant to form new supply chain relationships following a shock (e.g. a tariff) or when the risk of future negative shocks is high. Existing relationships may continue, if new forming new relationships is costly. Likewise, relationships that continue may recover more quickly in the future, whereas those that are broken may not recover at all.

Using the 2013–2019 LFTTD, we compare the margins of growth in country-product varieties that face tariffs in 2018-2019 to those that never faced new tariffs. Our representative regression takes the following form,

$$g_{cpt} = \beta_1 I\left(\Delta\tau_{pc} > 0\right) \times Post_t + \alpha_{ct} + \alpha_{pt} + \alpha_{cp} + \varepsilon_{cpt}, \tag{3}$$

which includes fixed effects for country-time (α_{ct}), product-time (α_{pt}) and a country-product panel ID, α_{pc}. Some product-country imports will eventual be hit with increased tariffs, denoted $\Delta\tau_{pc} > 0$, in 2018 or 2019. We use an indicator variable $I\left(\Delta\tau_{pc} > 0\right)$ to classify this subset of products and interact it with a binary $Post_t$ indicator for imposition of tariffs ($Post_t = 0$ for the years $t = 2013 - 2017$ vs. $Post = 1$ for the years $t = 2018 - 2019$).

We do not make any causal claims about these estimates, but note that this difference-in-differences regression framework compares import growth rates for product-country trade flows eventually hit by a trade war tariff to those never hit by higher tariffs. We use this framework to examine the overall import growth rate for an individual country-product (g_{cpt}) as a dependent variable as well as to separately examine each of the six margins described above. This provides estimates of the contribution from the linear decomposition of each margin, as the effects will sum to the total effect. We will control for unobserved variation at

[9] The increase in the "Net Entry-Exit" line in 2007 is attributable to the change in the LFTTD matching algorithm in 2007 that resulted in a larger number of importers being identified. See details (Kamal and Ouyang, 2020).

the country-time, product-time, and country-product level through fixed effects. Standard errors are clustered at the country-HS6 level.

As can be seen from Table 3, the average country-product flow facing new, trade war tariffs had a reduction in growth rates of 17 points relative to a non-tariffed imports. Since the coefficients of each of the 6 margins must add up to the total effect, the table also indicates that the combined "extensive margin" effects of importers adding/dropping suppliers and importers entering/exiting was responsible for 9 points of the relative decline in growth rates. Thus, over half of the reduction in import growth from the tariffs was due to importers dropping suppliers ($DROP$), foregone supplier additions (ADD), importer exit ($EXIT$) and foregone importer entry ($ENTRY$). On the intensive margin, trade creation in continuing relationships was 2 points lower and destruction was 5 points lower.[10]

We now explore how import growth and the various margins responded differentially to the import tariffs based on the level of foreign supplier concentration, HHI_p^S, of each product. The supplier-level concentration measure is a plausible way of distinguishing how imports may respond to trade shocks, as it proxies for the availability of alternative, similarly sized suppliers to which buyers may switch suppliers within a product. We therefore include our measure in a modified version of the regression above to generate a triple-interaction, using the HHI_p^S measure from the base year $t-1$:

$$g_{cpt} = \beta_1 I\left(\Delta\tau_{pc} > 0\right) \times Post + \beta_2 I\left(\Delta\tau_{pc} > 0\right) \times Post_t \times HHI_{p,t-1}^S + \alpha_{ct} + \alpha_{pt} + \alpha_{cp} + \varepsilon_{cpt}. \tag{4}$$

Table 4 reports the regression results. The first row confirms the earlier result that trade falls in products facing import tariffs, primarily as a result of extensive margin factors. However, the positive coefficient on the triple interaction in the first column of the second row indicates that among products facing new trade war tariffs, products with imports concentrated in fewer suppliers had a *smaller* decline in growth rates. To quantify these results, consider the fact that the averaged imported country-product in our regression sample has HHI_p^S very close to 0. Comparing the mean imported product to another product with an HHI_p^S one standard deviation away implies that the more concentrated product had about a 0.5 percent smaller decline in import growth.[11]

The additional columns of Table 4 illustrate that in more concentrated products, the negative contribution to import growth from the entry and exit of importers (the last two columns) is much weaker. This suggests that in response to import tariffs, concentrated

[10]Margins don't fully add up due to rounding at the hundredths place required for disclosure.

[11]The standard deviation of the HHI_p^S measure for our regression sample is about 0.1.

products have much less trade lost from importers exiting/foregoing entry. This evidence suggests higher foreign supplier concentration means starting new relationships or quitting existing ones, even where there is a cost shock like a tariff, is difficult when there are fewer short-term alternatives available.

In sum, our study of the supplier margins of sourcing indicates that buyer-supplier churning was a large contributor to import growth and declines. However, the degree of "foreign supplier concentration" matters, as adjustment is less possible for products where supplier concentration is higher. This suggests that for such products alternative foreign or domestic suppliers may not be available, leading improts to continue sourcing even in the face of the tariffs.

4 Export Responses to Import Tariffs

We now examine how supply chain adjustments from the 2018–2019 U.S. import tariffs affected U.S. exports. In this section, the key *importer–exporter* data linkage we consider is that of individual U.S. importing firms that also export. These are within firm linkages. By identifying the exporters, in 2016, that also imported products on which tariffs are ultimately imposed in 2018-2019, we construct measures of import tariff exposure for dis-aggregated export products. Combined with official monthly public-use export data from 2015 through 2019, we estimate the impacts of tariff exposure on U.S. exports.

4.1 Methodology

This section describes our methodology for measuring U.S. exported products' exposure to import tariffs. First, we define a measure of direct import tariff exposure of U.S. exporters, then extend to consider indirect exposure measures. The unifying theme of the exposure measures is that they map firm-level exposure to import tariff increases into disaggregated exported product level measures (i.e. 6-digit sub-headings of the HS).

4.1.1 Direct Import Tariff Exposure Measures

We refer to exposure measures constructed using firms that both import and export as "direct" in that we can observe exporting firms' import transactions. The key idea of the direct tariff exposure measure is to link exposure of firms subject to new import tariffs with the products they are exporting. This approach requires firm-level data to measure the incidence of tariffs and to weight the importance of each firm in product-level exports.

We proceed by assuming the effect on exports from the new import tariffs can be captured through the observable, direct linkages at firms that import and export. A large share of U.S. trade by value occurs at importer-exporter firms with trade participation rates that are persistent over time (Bernard, Jensen, Redding and Schott, 2018). We assume firm trade patterns in 2016, before the trade war or the election of Donald Trump, are representative of import-export linkages at the product level. This approach thus captures exposure to future tariffs, even if firms ultimately adjust their sourcing responses.

We start with a firm-level measure of the implied increase in tariffs on a firms' imports. Let Ω^M be the set of all importers. For each firm i in Ω^M, we can compute the change in implied duties paid, $\Delta duties_i^*$, and the duty share of total imports,

$$\Delta duties_i^* \equiv \sum_{rc} imports_{irc} \Delta \tau_{rc} \tag{5}$$

$$\text{AVE\_DutyShare}_i = \frac{\Delta duties_i^*}{\sum_{r,c} imports_{irc}} \tag{6}$$

where $imports_{irc}$ is 2016 imports for firm i of product r from country c and $\Delta\tau_{rc}$ is the maximum tariff increase in the 2018-2019 period. The duty share of imports, AVE_DutyShare_i has a natural interpretation as the ad valorem equivalent (AVE) tariff increase for each firm. It is bounded above at the maximum tariff increase in the data, 25% in this period, for firms that imported only tariffed product-country pairs, and bounded below at zero for firms that imported no products subject to new trade war tariffs.

To tie this measure to exports, we define the set of firms that export product p as Ω_p^X and we define import tariff exposure for p over the set of firms in the intersection $\Omega_p^{MX} \equiv \Omega_p^X \cap \Omega^M$. We weight AVE_DutyShare_i for each firm according to its contribution to total exports of product p in 2016 as follows:

$$ITE_p = \sum_{i \in \Omega_p^{MX}} \left[\frac{exports_{ip}}{exports_p} \times \text{AVE\_DutyShare}_i \right]. \tag{7}$$

Here $exports_{ip}$ is exports of firm i in product p, and $exports_p$ is total exports of p, both in 2016. Equation (7) is an export-weighted sum of AVE tariff increases faced by the set of firms exporting product p. The measure is an aggregation of the firm-level measure of AVE tariff increases in (6) for firms in Ω_p^{MX}, generating a product-specific import tariff exposure measure for product p, which we label ITE_p. Note that each firm in this set may be importing any number of products, potentially including product p itself. While individual firms may enter and exit international markets, it is reasonable to assume that population moments constructed from the cross-section of firm-level data are representative of firm trade participation at an aggregated product level.

This measure captures "direct" exposure because it is restricted to tariff changes faced by exporters that also import. Under this definition of exposure, 24% of all exporters were exposed to at least one new import tariff. These exporters accounted for 84% of total U.S. exports by value (Handley et al., 2020). An important advantage of this approach is that we can compute exposure at levels of aggregation with substantially more detail than industry codes. Our application will define p as a 6-digit (HS6) product, of which there are approximately 5,200. Given the broad coverage of intermediate goods subject to the 2018-2019 import tariffs, firm-level input supply chains were more likely to be directly affected relative to consumer products (Federal Register, April 6, 2018). Even if the tariffed goods are not inputs for some firm, exposure still measures costly frictions: higher duties paid, supplier switching costs, inventory adjustment, etc.

The tariffs were imposed in three broad tranches: solar panel and washing machine tariffs, metals tariffs, and tariffs on goods from China. We also define a tranche-specific import tariff exposure measure ($ITE_p^{T1}, ITE_p^{T2}, ITE_p^{T3}$) by modifying Equation (5) to only include τ_{rc} changes included in that particular tranche. These measures thus capture the exposure of U.S. exports to tranche-specific tariffs.

Though our baseline measure at the firm-level computes the AVE increase in tariffs on a firm's import expenditure, it is possible to consider an alternative to ITE_p by computing the variable cost share of higher tariffs. Detailed measures of total variable costs (i.e. labor, energy, materials, etc.) are not available for the universe of importing firms.[12] However, total firm payroll is available from the Longitudinal Business Database (LBD) for all employer firms operating in the United States (Chow, Fort, Goetz, Goldschlag, Lawrence, Perlman, Stinson and White, 2021). Combining payroll with firm import expenditure from the LFTTD means we can approximate the share of implied duties in variable costs (VC) as follows:

$$\text{VC\_DutyShare}_i = \frac{\Delta duties_i^*}{payroll_i + \sum_{rc}\left[imports_{irc}\right]}. \tag{8}$$

We then weight up at the product level using firms' 2016 export values as in (7) to obtain:

$$ITE_p^{VC} = \sum_{i \in \Omega_p^{MX}} \left[\frac{exports_{ip}}{exports_p} \times \text{VC\_DutyShare}_i\right]. \tag{9}$$

Of course, including payroll in the denominator of (8) will change the magnitude of

[12]Detailed input information is mostly available for the manufacturing sector in the Annual Survey of Manufactures and Census of Manufactures.

ITE. However, unless the respective contribution of payroll and imports to variable costs vary substantially across exposed firms, it should deliver similar estimation results to the baseline measure from above.

4.1.2 Indirect Import Tariff Exposure

Our direct ITE measures rely on data capturing within firm import-export linkages. But exports of product p can be indirectly exposed to import tariffs upstream in the supply chain through between firm buyer-supplier linkages. For example, some exporters may not import a tariffed product p directly but purchase it from intermediaries or domestic suppliers. These domestic suppliers may themselves be subject to new tariffs on their own imports or, alternatively, the tariff protection increases the equilibrium market price of domestic producers.

We construct two additional product-level measures to capture indirect import tariff exposure of a product: (1) the share of duties faced by importer-only firms; and (2) the share of duties that were transmitted to exports through input-output linkages, based on data from national input-output accounts.

Our first approach to indirect exposure focuses on the set of importer-only firms that import tariffed goods. We describe our construction of this measure and then its interpretation relative to the direct ITE_p measure.

In contrast to our direct importer-exporter firm exposure measures, where we link imports of all products r purchased by the exporters of product p, we do not observe direct links between importer-only firms' purchases and exported products. Instead, we aggregate the importer-only firm implied duties to exports in the same 6-digit product code p.

Formally, we define the set of firms that import product p as Ω_p^M, the set of firms that export as Ω^X, and thus the set of firms that import product p without exporting as $\Omega_p^{M\setminus X} \equiv \Omega_p^M \setminus \Omega^X$. Using these definitions, we construct the importer-only measure as follows:

$$\text{IMPONLY\_DutyShare}_{ip} = \frac{\Delta duties^*_{ip}}{\sum_i imports_{ip}}, \quad \forall\, i \in \Omega_p^{M/X} \tag{10}$$

$$ITE_p^{IMP} = \sum_{i \in \Omega_p^{M\setminus X}} \left[\frac{imports_{ip}}{imports_p} \times \text{IMPONLY\_DutyShare}_{ip} \right], \tag{11}$$

Similar to the interpretation of AVE_DutyShare_i, Equation (10) is a measure of the AVE increase in tariffs on all imports of product p for importer-only firms. But ITE_p^{IMP} differs from ITE_p because the firms in the set do not export. Thus, we weight up the duty shares by imports of the firms in $\Omega_p^{M\setminus X}$ to obtain the product-level exposure. This measure still differs from what could be obtained in public-use data because firm-level data is needed to identify the set of importer-only firms.

The importer-only measure is a proxy for how exposed the foreign-sourced supply of product p is to new trade war tariffs. For example, if all product p imports of importer-only firms originate from China and there was a 25 percentage point tariff increase, then $ITE_p^{IMP} = 0.25$. But if multiple other non-tariffed source country-product sources are available, the measure could be substantially lower. Following this interpretation, lower values of ITE_p^{IMP} are consistent with the Trump Administration's initial objective of targeting products where many foreign sourcing options, measured by value shares, were available.[13]

There are two indirect channels through which ITE_p^{IMP} could affect U.S. exporters. The first channel is that exporters that source their inputs of product p from importer-only firms may have faced supply chain disruptions and higher costs even though they do not import the products on their own account. Second, high values of ITE_p^{IMP} also proxy for the general equilibrium price increases in the market for product p, which could affect exporters even if they purchased from domestic producers.

Our second indirect measure captures exporters' indirect tariff exposure through economy-wide input-output (IO) linkages. We explain the main steps below and relegate other details to Appendix B.

Exporters may purchase products domestically that contain foreign content from upstream industries. To construct a measure reflecting this, we require "use shares" for each industry from the Bureau of Economic Analysis IO tables indicating the value of products in upstream industry k used in the production of downstream industry j. The use share is defined as:

$$use_{jk} \equiv \frac{inputs_{jk}}{inputs_j + comp_j} \tag{12}$$

where j denotes the using industry and k is the supplying industry; $inputs_{jk}$ is value of inputs purchased by industry j from industry k; $inputs_j$ is total input value (i.e. total intermediate input costs) in industry j, and; $comp_j$ is labor compensation in industry j. The term use_{jk} is the share of inputs used by industry j from industry k as a share of total variable costs in industry j.

[13]See U.S. Trade Representative Robert Lighthizer's testimony to the U.S. Senate Committee on Finance (2018).

Our input-output based ITE measure is then defined over all industries j, k that map into HS6 product p as follows:

$$\text{IO\_DutyShare}_j = \sum_{k \neq j} \left[use_{jk} \frac{\Delta duties_k^*}{imports_k} \right] \tag{13}$$

$$exports_{pj} = \sum_i exports_{ip} \quad \forall \text{ firm } i \in \text{industry } j \tag{14}$$

$$ITE_p^{IO} = \sum_j \left[\frac{exports_{pj}}{exports_j} \times \text{IO\_DutyShare}_j \right] \tag{15}$$

We thus construct a weighted sum of all duty shares for all industries k used for the production of industry j, IO_DutyShare_j, where the weights are the use shares of each industry k in industry j. Equation (13) excludes purchases from industry j itself since ITE_p and ITE_p^{IMP} already measure exporters' own-industry purchases.

Without firm-transactions data we could only map the IO duty share in (13), which is an industry aggregate, back to HS6 products using a concordance. Fortunately, we can go one step further and construct the product-level ITE_p^{IO} in (15) as an export weighted average using all firms that export HS6 product p, thereby using actual links between exports and firms' main output industries we observe in the data. This is particularly important where firms in multiple industries export the same HS6 product, a common situation which does not conform to concordances that uniquely match an HS6 product code to a single NAICS industry.

For constructing the baseline ITE_p measure, we identify firms trading products that face import tariffs in 2018-2019 by linking confidential goods trade transactions by U.S. firms directly to products subject to newly imposed import tariffs. We combine information on the value of Harmonized System (HS) products imported ($imports_{ir}$) and exports ($exports_{ip}$) by U.S. firms in the 2016 LFTTD with payroll ($payroll_i$) from the 2016 LBD. We obtain industry use shares from the Bureau of Economic Analysis use tables (see Appendix Section B for details).

4.1.3 Difference-in-Differences Framework

Our estimation approach begins with the premise that trade flows have a standard gravity form, meaning we can decompose bilateral exports (in logs) of the country implementing import tariffs as follows,

$$\ln Exports_{pct} = \theta_\tau \ln (1 + \tau_{pct}) + \Gamma_t ITE_p + \alpha_{pc} + \alpha_t + \epsilon_{pct} \tag{16}$$

where $\ln Exports_{pct}$ is log value of a country's exports of a product p to destination c in month t.[14] Foreign export tariffs are the natural log of 1 plus the *ad valorem* tariff level faced by exports to destination country c. The product level, time-invariant regressor ITE_p measures exposure to new tariffs. The response of exports to ITE_p can vary over time through the coefficient Γ_t. The baseline ITE_p measure is as defined in Equation (7). In alternative specifications, we other exposure measures as defined in Equations (9), (11) and (15). The α terms are fixed effects for a country-product panel identifier (pc) and month (t).

Our approach aims to estimate the supply chain impact after a period of tariff escalation begins relative to the period before the tariff escalation, so we interact ITE_p with an indicator for whether time t is before or after the start of tariff increases in January 2018, $I(t \in Post)$. We thus implement a generalized difference-in-differences strategy to estimate whether exports in products with higher exposure to import tariffs, the first difference, is lower in the post-tariff period relative to the pre-tariff period, the second difference. Our estimation equation is

$$\ln Exports_{pct} = \theta_\tau \Delta \ln(1 + \tau_{pct}) + [\Gamma_1 - \Gamma_0] ITE_p \times I(t \in Post) + \alpha_{pc} + \alpha_t + \varepsilon_{pct} \qquad (17)$$

where we denote pre-period average of coefficients with subscript 0 and post-period with subscript 1. Thus $\Gamma_0 = \overline{\Gamma}_t$ for all months prior to January 2018 and $\Gamma_1 = \overline{\Gamma}_t$ for all subsequent months.

The primary coefficient of interest estimates the difference in exports from pre- vs. post-trade war periods to the level of import tariff exposure, $[\Gamma_1 - \Gamma_0]$. This difference is negative if $\Gamma_1 < \Gamma_0$, indicating that exports are lower in the post-period when the tariffs are implemented. Because the specification includes product-country α_{pc} fixed effects, the pre-period coefficient Γ_0 on ITE_p is not identified. Thus our eventual quantification of the impact of tariff exposure compares more versus less exposed products. The omitted Γ_0 coefficient can be thought of as the effect of future tariff exposure on pre-trade war exports. For example, this may capture the effect of overall supply chain sensitivity of export growth in the period before the tariffs were imposed. This effect is also likely to be correlated with other unobserved product characteristics that influenced export growth. Thus, we also check for potential pre-trends in an event study framework in section 4.3.2.

[14] We examine total exports—both domestic and foreign exports. Domestic exports are goods grown, produced or manufactured in the U.S.; foreign exports are goods of foreign origin that are "re-exported" in substantially the same condition as when imported. Weak export growth is not being driven by a reduction in foreign exports because domestic exports account for about 85% of overall exports. Total and domestic export growth between 2019 and 2018 were almost identical.

In our preferred, baseline version of the estimating equation, we include several additional sets of fixed effects and write the coefficients and indicators as follows:

$$\ln Exports_{pct} = \theta_\tau \ln(1+\tau_{pct}) + [\Gamma_1 - \Gamma_0] ITE_p \times I(t \in Post) + \alpha_{pcm} + \alpha_{sct} + \varepsilon_{pct}. \quad (18)$$

To handle seasonality present in monthly trade flows, we further saturate equation (17) by fully interacting product-country variety fixed effects with a set of 12 calendar-month indicators α_{pcm}.[15] The panel identifier is thus effectively a product-country-calendar-month cell. We also include sector-country-time fixed effects α_{sct} where we define a sector in the baseline regression as the 2-digit chapter (HS2) of the product. Together, these fixed effects control for unobserved time-varying destination factors (e.g. exchange rate fluctuations, trade barriers, and foreign demand shocks), sector specific shocks to a country's export supply or foreign import demand, and other time-varying country-product shocks.

We examine the aggregate response of all U.S. exports to import tariff exposure through ITE_p by estimating equation (18) using weighted least squares with country-product export values as weights. Specifically, the weights are the average annual HS6 product-destination exports between 2014 and 2016. This specification gives greater weight to product-destination trade flows with higher pre-period exports and helps ensure that the results are not driven by large export responses to small export markets. The denominator in our product-level ITE_p measure from Equation (7) is total exports of p. The export weighted mean of ITE_p simply renormalizes by total exports and thus is naturally interpreted as the aggregate import tariff exposure of U.S. exports.

4.2 Summary Statistics

The product-level import tariff exposure measures are time-invariant and constructed using moments from firm-level trade flows in 2016 and, hence, should not be influenced by the 2016 presidential election or anticipation of tariffs in 2017.[16]

The most and least exposed products according to our baseline ITE_p measure are consistent with the emphasis on intermediate inputs, as shown in Table 5. We measure exposure of an HS2 chapter by taking the share of HS6 products in each HS2 with an ITE_p greater than the median of the distribution (i.e. chapters with a large number of highly exposed products). The five most exposed 2-digit HS Chapters represent a third of all U.S. exports

[15] For example, a sample value of t would be January 2019, while a sample value of m would be January.

[16] The outcome of the 2016 U.S. presidential election was a surprise to many observers. It is unlikely affected industries could have anticipated the tariff changes or made major adjustments in the final 6-7 weeks of 2016.

in 2016. They are export products related to machinery and equipment (chs. 84 and 85), iron and steel products (ch. 73), chemicals (ch. 26), and various optical, photographic, and medical instruments (ch. 90). The five least exposed products include articles of lead and tin (chs. 78 and 80), feathers and artificial hair (ch. 67), live trees (ch. 6), and milling products (ch. 11).

Table 6 reports the mean and associated standard deviation of the data underlying our regressions. The data we use is public-use monthly U.S. export data by destination and HS6 product from 2015 through 2019 sourced from the U.S. Census Bureau (U.S. Census Bureau, 2019). We report weighted means and standard deviations of the variables over that sample using the regression export value weights described above.[17] As shown in the table, the weighted mean of ITE_p is 0.02, which implies an increase in costs of 2% of imports for importer-exporter firms. The mean value of ITE_p^{VC} is half that, 0.01, because it includes a normalization by total imports *and* payroll.

We also report the mean and standard deviations associated with exposure to the different waves of tariff increases. Recall that there were three broad tranches of tariffs. As shown in Table 6, the means of the direct exposure measure for Tranche 1 (solar panels and washing machines) tariffs, ITE_p^{T1}, and Tranche 2 (steel and aluminum products) tariffs, ITE_p^{T2}, are both very small in the regression sample. The sample average for ITE_p is driven by Tranche 3, ITE_p^{T3}, which includes all the waves on imported Chinese goods. The third wave of tariffs were imposed on almost half of all imports originating in China, particularly targeting intermediate goods. While the first two tranches have small means in the overall sample, we find large impacts on affected sectors in the regression analysis.

Retaliation by foreign countries was a major feature of the trade war, and exports are known to have fallen significantly in response to such retaliation ((Fajgelbaum, Goldberg, Kennedy and Khandelwal, 2020)). We thus also build a dataset of retaliatory foreign export tariffs at the 6-digit HS (HS6) level to use as controls, using the timeline from Bown and Zhang (2019). The trade-weighted average tariff increase from retaliation is about 20 percentage points.[18]

Table 6 also summarizes the other variables in our regression, namely the dependent variable—log monthly U.S. exports by destination and product– and the level of export tariffs for each destination country and products. Averaging over the entire sample period from 2015 through 2019, log monthly U.S. exports have a trade-weighted mean of 16 and a

[17] Even though the ITE_p measures are not time-varying, the means and standard deviations over our regression sample differ somewhat from the static numbers due to the fact that not every HS6 product is exported to every country every month, thereby changing the distribution of the measure in the sample.

[18] Additional details in Appendix B.

standard deviation of 2.5; the trade-weighted mean of retaliatory tariffs on exported products is about 4 percent. During the trade war period of 2018-2019, the level of exports was much lower while the level of retaliatory export tariffs was much higher compared to earlier years.

4.3 Results

We begin by exploring export dynamics from 2015-2019 period and highlight the decline in exports after the trade war begins using reduced form and event study frameworks. We then turn to our generalized difference-in-differences specifications, sources of heterogeneity, and robustness exercises.

4.3.1 Semi-parametric Motivating Evidence

Before we turn to our baseline difference-in-difference regression analysis, we establish a clear reduction in exports following the onset of the trade war. The decline is large, significant, and that it cannot be fully explained by seasonality or retaliatory tariffs.

We begin with a simple specification that only includes controls for export tariffs and product-country seasonality. We estimate the following regression by weighted least squares:

$$\ln Exports_{pct} = \theta_\tau \ln(1 + \tau_{pct}) + \alpha_{pcm} + \varepsilon_{pct}. \tag{19}$$

Next, we save the residuals from this regression and compute their trade weighted mean by month. There is a large drop in this measure of deseasonalized, residual exports, even after controlling for retaliation. Figure 2 plots a local polynomial through the residuals from estimating (19).[19] The mean of these residuals before 2018 is about 1 log point (dashed, horizontal line). The fall of the residual exports below the pre-period mean coincides with waves 2 and 3 of the China tariff tranches, but may also reflect the lagged impact of previous waves. By 2019, the monthly export residuals are clearly negative relative to the pre-period suggesting that factors other than retaliatory tariffs and seasonality are associated with weaker exports.

Having established that exports declined after the imposition of tariffs in 2018, we show this reduction is statistically significant in 2019 relative to the entire pre-period by estimating the following specification:

$$\ln Exports_{pct} = \theta_\tau \ln(1 + \tau_{pct}) + \beta_{2018-0} I(2018) + \beta_{2019-0} I(2019) + \alpha_{pcm} + \varepsilon_{pct}. \tag{20}$$

[19] This regression only uses public-use export data on monthly flows and tariffs.

The β_{yyyy-0} coefficients identify the annual mean difference in exports in 2018 and 2019 compared to the pre-period. If we omit the control for export retaliation, then there is no effect in 2018 and a 7.5 log point decline in 2019 relative to the pre-period. When we include tariff controls, we again find no effect in 2018, $\hat{\beta}_{2018-0} = 0.003$. But in 2019, the difference is over 5 log points and statistically significant ($100 \times \hat{\beta}_{2019-0} = -5.2$ with a t-stat of -6.5).

In sum, the pre- vs. post-trade war export differential in our sample is large and negative. Our objective in the following empirical sections is to show that relative differences in ITE_p explain part of the residual difference, even after we control for tariff retaliation, seasonality, and a full set of sector-country-time shocks.

4.3.2 Event Study Evidence

We implement an event study specification that allows us to confirm the absence of pre-trends and examine anticipatory or phased-in responses to the import tariff increases.

Rather than pooling estimated effects as in the generalized difference-in-differences framework defined in (18), an event study specification allows the coefficient on ITE_p to vary by quarter from 2015q1 to 2019q4.

$$\ln Exports_{pct} = \theta_\tau \ln(1+\tau_{pct}) + \sum_{\substack{q=2015q1 \\ q\neq 2017}}^{2019q4} \Gamma_q ITE_p \times I[Q(t)=q] + \alpha_{pcm} + \alpha_{sct} + \varepsilon_{pct}, \quad (21)$$

where $I[Q(t) = q]$ is a set of binary quarterly indicators and $Q(t)$ maps monthly data into its respective quarterly running variable (e.g. $Q(2019m12) = 2019q4$). Because we include country-product-calendar-month effects for seasonality, the entirety of 2017 is the omitted reference period. Thus, Γ_q is the estimate of ITE_p for each quarter relative to 2017. Figure 3 presents the quarterly coefficients on *direct* import tariff exposure, ITE_p, from estimating Equation (21), with the gray band denoting 2017.[20]

We find no evidence of a pre-trend in the exposed level of products and the impact of import tariff exposure on exports only becomes negative in 2019 when all the import tariff waves were finally implemented. We find that seven of the eight Γ_q coefficients in 2015 and 2016 are close to zero and statistically insignificant. After 2017, we begin to see evidence of a dampening effect of import tariffs on exports particularly in late 2019 when half of all Chinese imports were subject to a tariff increase. We find negative and statistically significant impacts by the second half of 2019 after the escalation of wave 3 tariffs on China

[20] A monthly event study specification shows the same patterns, but is noisier and less informative. The quarterly coefficients are pooled averages of the monthly counterparts.

from 10% (vertical line marked ‘E’) to 25% (vertical line marked ‘F’). The coefficients in 2016 do not suggest anticipatory effects relative to 2017.[21]

To validate whether our measure of exposure contains useful variation across products, we run a similar event study after splitting the sample into above and below median ITE_p. In the top panel of Figure 4 we plot the coefficients for high (above median) exposure relative to less exposed products. We again find no evidence of a pre-trend before 2018 and a clear reduction in exports by 2019. The coefficient estimates in the bottom panel for low exposure products are noisier. These exported products are still exposed to import tariffs and they do tend be more negative in 2019. Comparing panels (a) and (b) we find the average ITE_p coefficient in the above median sample is -2.47 in 2019. This is about 40% higher than the average coefficient for low exposure of -1.75 over the same period.

4.3.3 Direct Import Tariff Exposure Estimates

We next present results from the generalized difference-in-differences specification as described in equation (18) that also indicates a negative relationship between direct exposure to import tariffs and exports. We then provide additional results exploring heterogeneity and robustness of this finding.

We report our baseline findings in Column 1 of Table 7. The implied elasticity of retaliatory tariffs on U.S. exports is about -1.4, in line with Fajgelbaum et al. (2020). The coefficient on the *direct* import tariff exposure measure, ITE_p, is strongly negative in the trade war period—products with higher tariff cost shares experienced lower exports.

In the second column we confirm that the results are robust to an even more saturated set of fixed effects. We continue to include destination country-HS6-calendar month, but further saturate country-sector shocks with country-HS4-month fixed effects. The coefficient on ITE_p almost triples compared to the baseline estimate in Column 1. This is not our preferred specification because 25% of the sample is dropped and the remaining pre vs. post comparison cells are potentially quite small.[22]

We also check that our main results are not driven by using weighted least squares regressions. Weighted regressions coefficients could be driven by only a handful of very high value trade flows and thus be unrepresentative of the conditional mean effects for the average exported product. We confirm that the results are robust to weighting in Table 5, Column

[21] Anticipatory effects would bias estimates in the 2018-2019 post period toward zero.

[22] There are more than 10 times as many 4-digit headings as there are 2-digit chapters of the HS. This is one reason why the export tariff coefficients substantially drop. There simply is not enough variation in tariffs within narrow country-HS4-month cells.

3 where we run OLS on Equation (18). The estimated negative impact on exports from ITE_p is nearly unchanged when comparing to Columns 1 and 3. The export tariff elasticity falls, which may be the result of the composition of products targeted by foreign retaliatory tariffs.

A final threat to identification may be posed by time-varying factors at the country-product level that are also correlated with ITE_p. In this case, we may find a negative differential relationship between exports of high compared to low exposed products even where one does not exist. In Column 4 of Table 5 we run a placebo test on data from 2013 to 2017. We keep the exposure measure for each product the same but turn on the post indicator for all observations in 2016 and 2017. All of the export flows in this regression are *before* the trade war tariffs were actually implemented. We find that the coefficient on ITE_p is positive and only marginally statically significant at the 10% level. This suggests that, prior to the trade war, products with higher shares of imports eventually hit by tariffs actually had higher exports. Thus, we can rule out a there is negative relationship between ITE and exports driven by other correlated factors in our specification. We also note there is no effect of tariffs on exports for the entire period 2013-2017. Before the trade war retaliation is implemented by trade partners, there is very little residual time variation in tariffs to identify the coefficient, especially on an export weighted basis.

4.3.4 Timing and Heterogeneity in Tariff Waves

We now explore the timing and heterogeneity in the estimated reduction in exports due to import tariff exposure.

We begin by separating the effects of direct exposure to import tariffs in 2018 and 2019. The event study, as shown in Figures 3 and 4, clearly suggest the dampening effect of ITE_p on exports takes time. In Table 8 we interact ITE_p with indicators for 2018 and 2019 given by $I(yyyy)$. The effect of the exposure to import tariffs are much more negative in 2019. For our baseline set of fixed effects, all of the impact occurs in 2019. When we nearly saturate with country-HS4-month fixed effects in Column 2, we see some negative and significant impact in 2018 as well. Similarly, in the unweighted Column 3 coefficients, the impact on the average product is already evident in 2018 and nearly doubles by 2019. The larger impacts in late 2019 are consistent with additional tariff waves being added throughout 2018 and large escalation in tariff levels on Chinese goods in May 2019. We expect a smaller initial effect in 2018 since our ITE measure incorporate all newly-imposed tariffs through May 2019, regardless of their timing. The results suggest importer-exporter firms took time to adjust, which may be due to running down existing inventories, adjustment and switching costs, and uncertainty about how long the tariff increases would remain in place.

To further unpack details of the timing and the country or product targets of tariffs, we divide our tariff exposure measure into three tranches in Column 4 of Table 8. Exposure to tariffs in Tranche 1 (solar panels/components and washing machines), Tranche 2 (aluminum and steel) and Tranche 3 (Chinese imports targeted under Section 301) all exhibit negative effects on U.S. exports, but the Tranche 2 metals tariffs are not significant. The insignificance of the metals tariffs may reflect that many of the tariffed products were homogeneous products (e.g. cold-rolled steel coils) where U.S. domestic or non-tariffed foreign sourcing could meet demand.[23] The coefficient is large and negative for Tranche 1, but the overall exposure of exporters to these tariffs was small, and nearly zero on an export weighted basis as shown in Table 6. Using one standard deviation unit of the Tranche 3 measure for comparison, the standardized coefficient on Tranche 1 is $-0.106(= -17.98 \times 0.0001/0.017)$. The standardized coefficient for Tranche 2 is $-0.173(= -1.471 \times 0.002/0.017)$. Comparing these standardized coefficients, with the Tranche 3 coefficient of -0.642, it becomes clear that changes in exposure to the China tariffs had a larger effects on exports.

The final two columns of Table 8 split the sample into high and low exposure by the median of ITE_p, as in the event study estimates presented in Figure 4. Underscoring again the information content of the ITE_p measure, the negative effects are driven more by the set of exporters of products that faced higher exposure to import tariffs. While the coefficients on above and below median exposure are clearly statistically different, we note that the estimated export tariff elasticities are nearly the same across the samples, but slightly lower than the pooled baseline elasticity from Column 1, Table 7.

Table 9 shows the results of a number of robustness exercise alongside the results of our main specification. We first present results from using our measure of exposure using tariffs as a share of "variable costs"– ITE_p^{VC} defined in Equation (9). Similar to above, the regression results in Column 2 of Table 9 imply that a one standard deviation shock to ITE_p^{VC} implies a 1.66 log point reduction in exports whereas the same shock to ITE_p generates a 1.11 log point effect.[24] Next recall that the Trump administration had a strategic focus on China and actively promoted re-shoring of U.S. activities in China to the U.S. This might have generated a large impact on two-way trade between China and U.S. leaving other bilateral relationships unaffected. To check whether our results are driven primarily by the interaction between tariff exposure and exports to China, we drop all exports to China from our sample in Column 3, Table 9. The coefficient on ITE_p is -0.701, which is only slightly

[23] Amiti, Redding and Weinstein (2020) find metals tariffs had less than 100% pass through to prices, which is not the case for most other industries.

[24] The calculations are $-0.657 \times 0.017 = -0.0111$ (Column 1); $-1.511 \times 0.011 = -0.0166$ (Column 2).

more negative than the baseline effect of -0.657. This underscores our story that import tariff exposure spilled over into other markets. We also note the coefficient on export tariffs falls because China makes up a large share of U.S. exports subject to tariff retaliation. Lastly, we also check whether the results are being driven by targeted retaliation against specific exported products that may happen to be subject to high exposure. In Column 4, we drop all products ever subject to any tariff retaliation. The coefficient on ITE_p becomes slightly more negative and remains statistically significant.

4.3.5 Estimates of Indirect Import Tariff Exposure

Thus far, we find evidence that *direct* exposure to import tariffs through exporters' purchases of tariffed imported goods depressed U.S. exports. We now estimate the export effects of including *indirect* import tariff exposure measures.

Table 10 reports the results using two measures of *indirect* exposure to import tariffs described in Section 4.1.2: importer only exposure (ITE_p^{IMP}) and input-output exposure (ITE_p^{IO}). In Column 2, we include both ITE_p and ITE_p^{IMP} and find that the coefficient on ITE_p is slightly smaller compared to our baseline estimate in Column 1 of Table 7 (-0.657 vs. -0.482), but remains negative and statistically significant. The coefficient on ITE_p^{IMP} is -0.254 and statistically significant.

The ITE_p^{IMP} measure is a proxy for exposure of exporters that purchase imported inputs from other firms in the same 6-digit product sub-heading as the exported good. Because ITE_p and ITE_p^{IMP} are obviously correlated, independently shifting one measure is conceptually feasible but practically impossible. Nevertheless, taking the coefficients from Column 2, moving from zero exposure to the mean of either ITE_p or ITE_p^{IMP} would deliver the same 0.9 log point relative decline in exports.

We also note that including ITE_p^{IMP} may also proxy for equilibrium price increases in the inputs for exporter firms that source from domestic producers or other importers. These equilibrium price effects may not be fully absorbed by the more aggregate sector-country-month fixed effects. So another interpretation of the the results in Column 2 (and 3) is that the baseline estimates of the ITE_p coefficients is robust to general equilibrium price effects in the same product.

An important caveat to interpretation of ITE_p^{IMP} as an indirect measure of exposure is that it can only link imports and exports in the same product p category. Effectively, it is measuring the diagonal of a hypothetical input-output table with over 5,000 rows and columns. Our preferred ITE_p measure already incorporates very detailed information on observed import-to-export supply chain linkages within firms of the diagonal and off-diagonal relationships. Thus it should already be a good proxy for unobserved indirect linkages as well.

We find some evidence for this interpretation using the coefficients in Column 2 of Table 10. The omitted variable rule implies a coefficient of 0.69 from a residual regression of ITE_p^{IMP} on ITE_p.[25] Thus, 69% of a unit shock to the baseline ITE_p measure is reflected, conditional on all controls, in the importer-only measure measure. The reduction in magnitude in the ITE_p coefficient from Column 1 to 2, is found by multiplying $0.69 \times (-0.254)$. Thus, interpreting the reduction in the baseline ITE_p coefficient from including ITE_p^{IMP} in Column 2 is complicated, especially if ITE_p^{IMP} is introducing more noise than signal.

In the last column we add the IO measure, ITE_p^{IO}, intended to capture economy-wide input-output linkages. The coefficients on ITE_p and ITE_p^{IMP} remain almost identical to that in Column 2. The IO measure has a mean of 0.007, which is roughly the implied duty share of the tariff increase to indirect total costs by industry. This measure is insignificantly different from zero in our regression.

Our estimation approach is not designed to rule-in or rule-out one measure over another. But the limited explanatory power of ITE_p^{IO} suggests that the linkages we observe at the firm-level for importer-only and importer-exporters already capture the primary channels through which import tariffs dampen U.S. exports. Additionally, the IO measure is constructed from 405 aggregate industry codes and only has 6-digit HS product level variation in the cross-section due to weighting up by export values. Where the exports of a particular product are dominated by one industry or several neighboring industries with similar IO structure, there may not be sufficient residual variation, conditional on fixed effects, to identify the coefficient.

4.4 Quantification

We present two quantification exercises to better understand the economic magnitude of the export impact of exposure to increases in U.S. import tariffs. First, we calculate the contribution of exposure to import tariffs on the post-trade war decline in aggregate exports. Next, we calculate the *ad valorem* equivalent of the estimated impact of exposure to import tariffs on exports.

4.4.1 Comparisons to post-2018 Decline in U.S. exports

We make relative comparisons of the effect on exports of products in high versus low import tariff exposure. Then we compare the magnitude of the differential reduction to the aggregate

[25] We employ the simple omitted variable rule formula expressing the coefficient in Column 1 as the linear combination $\Gamma_1 = \tilde{\Gamma}_1 + c \cdot \Gamma_{IMP}$ where $\tilde{\Gamma}_1$ and $\tilde{\Gamma}_{IMP}$ are the coefficients from Column 2. The coefficient c is obtained by regressing ITE_p^{IMP} on ITE_p with all other controls included, i.e. a residual regression.

export decline in 2019.

A full counterfactual would require Γ_0, which measures the effect of importer-exporter linkages measured by ITE_p in the pre-period. As noted in Section 4.1.3, we cannot identify the pre-trade war effect of ITE_p, i.e. the coefficient Γ_0 in Equation (18). Because our measure does not vary over time, we rely on the identifiable change in the Γ coefficient on ITE_p.

The weighted average exposure measure in our sample is 0.0193—the aggregate export weighted AVE of the implied duty increase. Comparing products with average exposure to zero exposure, the difference in annual average exports is a 1.3 log point decline at the mean using estimates in Table 7, or $(-0.657 \times 0.019) \times 100$. The standard deviation of the ITE_p measure is 0.017. This implies that the difference moving from one standard deviation below the mean to one standard deviation above, a shift of $2 \times 0.017 = 0.034$, translates into a 2.2 log point reduction in exports when exposure is high relative to low (-0.657×0.034). However, we also know from the results above that most of the impact of the tariffs was not realized until 2019. If we compute the effect as of 2019, using the coefficients in Table 8, Column 1, the effect is a 2.9 log point reduction at the mean relative to zero and over 5 log points for a two standard deviation shift.

We argue that these magnitudes are meaningfully large, given the observed weakness is U.S. exports in 2019, even though we cannot run a direct counterfactual exercise. In Figure 2, we found 5.2 log point differential reduction in the 2019 unexplained export residuals relative to the pre-period. Our regression approach in Table 8 provides an estimate of how much of this 5.2 log point average time difference can be explained by relative differences in ITE_p, after conditioning on controls. Our estimate of the differential at the weighted mean of ITE_p is -2.9 log points, which is over half the unexplained export differential from Figure 2. Most of the remaining differential is due to unobserved time-varying shocks absorbed by our sector-country-time fixed effects.[26]

4.4.2 *Ad valorem* tariff equivalent of ITE

We calculate the *ad valorem* equivalent (AVE) tariff on exports stemming from U.S. import tariffs to compare estimates of import tariff exposure to foreign retaliatory export tariffs.

[26]We also note that if we omit export tariffs from the regression in (20), the differential reduction in 2019 exports is more than 7 log points. This differential is almost perfectly explained by multiplying by weighted average change in tariffs between 2019 and the pre-period by the estimated tariff elasticity, (i.e. $\theta(\mathbb{E}[\ln(1+\tau_{pct}) \mid t \in 2019] - \mathbb{E}[\ln(1+\tau_{pct}) \mid t < 2018])$). Thus, of the total average, deseasonalized export differential in 2019 relative to the pre-period about 1/3 is retaliation, 1/3 is ITE, and 1/3 is other unobserved supply and demand shocks.

We begin by plotting estimates of the export tariff elasticity, θ_τ in equation (21), from 2015 through 2019 as shown in Figure 5. Essentially, the question is whether the export tariff elasticity during the retaliation period is fundamentally different than the pre-period. Looking at the quarterly coefficients in 2015 and 2016 we find that, with the exception of 2015Q1 and 2015Q4, all coefficients are statistically indistinguishable from zero. After 2017, we find that most coefficients are negative and statistically significant.

The main factor that drives the elasticity to be different in the pre- and post trade war period is that there is very little variation in tariffs faced by U.S. exporters until the trade war. Because our regression includes country-HS6-calendar month effects and sector-country-month effects, we require time variation in foreign tariffs for identification. As we have already seen in results above, the estimated tariff elasticity is also sensitive to further saturation in the fixed effects relative to our baseline (see Table 7).

In Table 11 we investigate this further by interacting the tariff elasticity with the same binary post indicator we use for ITE_p. In contrast with the event study in Figure 5, the omitted comparison group is not each month in 2017. We are simply checking whether the elasticity is significantly higher during the trade war. Comparing Columns 1 and 2 for our baseline weighted regression, we confirm that the export tariff elasticity is higher during the trade war period, a post elasticity of -1.452 vs -1.237 in the pre-period. When we saturate the fixed effects on Columns 3 and 4, the elasticity goes down in magnitude and the post-effect is no longer significant. In unweighted regressions, we also find a significantly higher post trade war elasticity (Columns 5 and 6).[27]

We compute *ad valorem* equivalent of import tariff frictions on supply chains, τ^{AVE}, using the estimated coefficients on the *direct* import tariff exposure measure $(\Gamma_1 - \Gamma_0)$ and the elasticity of the retaliatory tariffs (θ_τ) as follows:

$$\tau^{AVE} = \exp\left(\frac{(\Gamma_1 - \Gamma_0) \times ITE_p}{\theta_\tau}\right) - 1. \tag{22}$$

This measures the change in foreign tariffs on U.S. exports that would generate an equivalent change in exports at different levels of ITE_p.

We start with a conservative estimate of the AVE tariff of import tariff exposure. We use the coefficient on retaliatory export tariffs from the baseline specification, -1.425, and the ITE_p coefficient of -0.657 from Column 1 of Table 7. At the mean of $ITE_p = 0.019$ the AVE tariff is 0.86% ($= \exp(\frac{-0.647\times 0.019}{-1.425}) - 1$), or close to 1%. This is conservative for two

[27] When country-product-calendar month and country-HS4-month effects are combined, we absorb over 99% of the retaliatory tariff variation.

reasons. First, we are using the pooled effect over the entire 2 year period and the larger impacts occur in 2019. Second, the we are using an elasticity of exports to tariffs on the higher end, in absolute magnitude, of our estimates for this parameter. The more responsive exports are to tariffs, the smaller are the AVEs.

Our preferred estimate of the AVE tariff uses the estimated coefficients from Table 8, Column 1, that breaks out coefficients into 2018 and 2019. Using an estimated effect for all months in 2019 averages out any remaining seasonality and all new import tariffs are in place for most of that year. The AVE export tariff for a product with the mean level of ITE_p in 2019 is a 2% tariff. For products at the mean plus one standard deviation of the baseline exposure measure, in 2019, the τ^{AVE} is almost 4%. Figure 6 plots the AVEs using both the pooled and 2019 coefficients, marking off the mean plus one and two standard deviations on the horizontal axis. These AVE tariffs are large in two ways. First, the *export weighted average* increase in tariffs on all goods that we observe in the data is 1.2%. Thus, by 2019, the additional reduction in U.S. exports through ITE_p is larger than the effect of all retaliation combined. Second, the 2% equivalent tariff at the mean is comparable to the trade weighted average of the U.S. statutory Most Favored Nation tariffs.

5 Conclusion

In this paper, we study firm-level supply chain adjustments during the 2018–2019 trade war. We study adjustments in U.S. imports as well as the downstream effects on total U.S. exports in response to the tariff shock. We rely on import flows between U.S. buyers and their foreign suppliers to examine the margins of adjustments in U.S. import growth and rely on U.S. exporters' import flows to capture the exposure of U.S. exports to the tariff increases.

We show that over half of the fall in U.S. imports targeted by new tariffs relative to non-tariffed imports stems was due to reduced (extensive margin) dynamism. Specifically, from an increase in importers dropping suppliers, from foregone supplier additions, outright exit of firms from participation in import markets, and foregone importer expansion into new foreign supplier markets. This implies that the effects of the tariffs are could be be long-lasting where there are substantial sunk cost to forming new buyer-supplier relationships.

We also demonstrate that in products featuring higher "foreign supplier concentration", the negative contribution to the change in growth from the entry and exit of importers channels is much weaker. This suggests that in response to import tariffs, the reduction in import growth was lower where products were concentrated in fewer suppliers. The latter may imply the reallocation of imports away from tariffed products will occur more slowly where foreign suppliers are limited in number and more highly concentrated. This may reflect a lack of alternative suppliers, which makes it harder to both stop buying from existing suppliers and start new relationships.

We also construct import tariff exposure measures from firm-level data for over 5,000 detailed HS6 products that capturing the import-to-export linkages of tariff increases implemented from from 2018-2019. Using our exposure measures, we show that the 2018-2019 trade war significantly dampened U.S. exports through supply chain spillovers. We implement a novel approach combining detailed firm-level trade transactions data with higher frequency public-use trade data to estimate near contemporaneous impacts of trade policy.

Our results suggest that the large share of new intermediate input tariffs in the 2018-2019 trade war spilled over into economic activity in many different products. Given the reduction in imports of tariffed goods we find, our results suggests many firms adjusted by reducing output in the short-run. The quantitatively large effects indicate the important role of large, importer-exporter firms that mediate most U.S. trade transactions. Future work could extend our method to inform and evaluate policies in other economic applications both as they are implemented or in targeting policy based on *ex-ante* production linkages that are not observable in more aggregated data.

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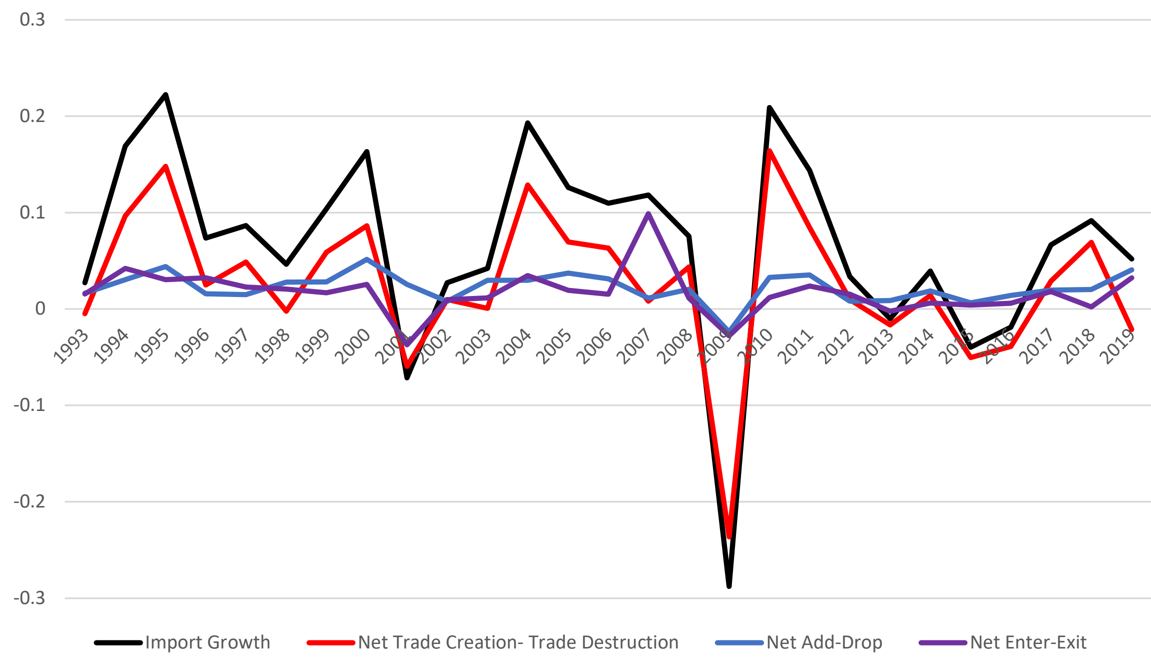
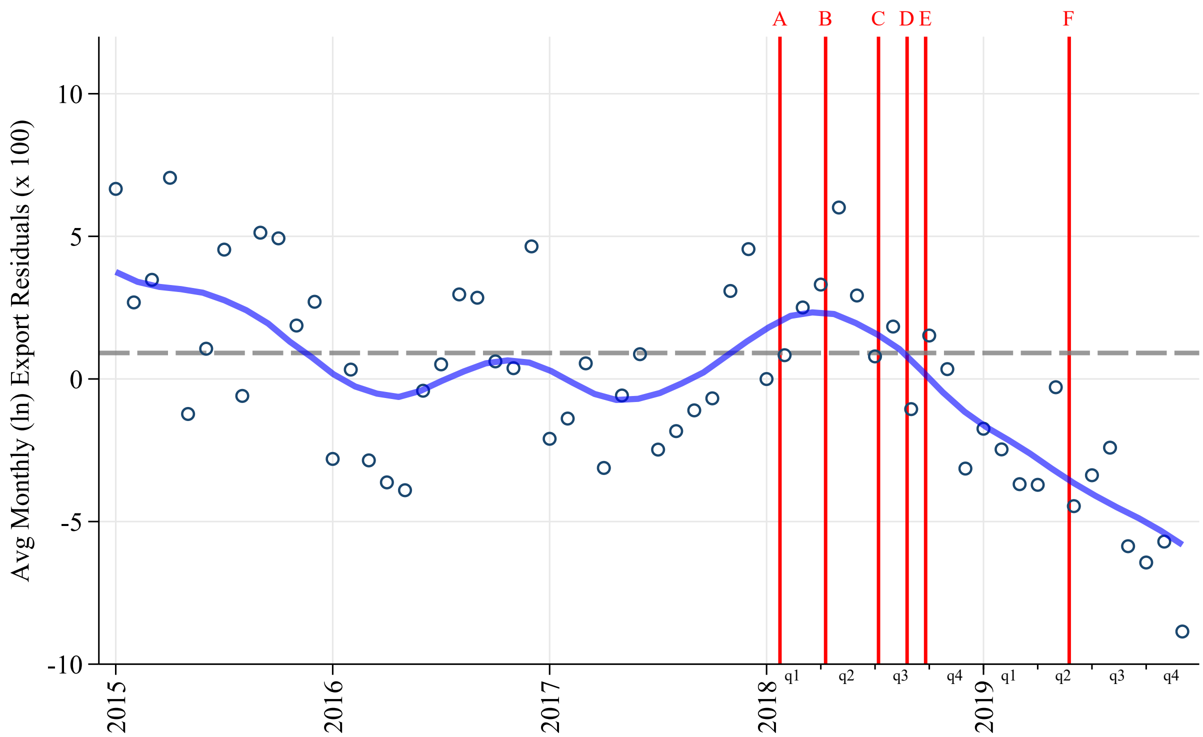
Figure 1: Annual import growth rate margins, 1993-2019



Source: Authors' calculations using 1992-2019 LFTTD.

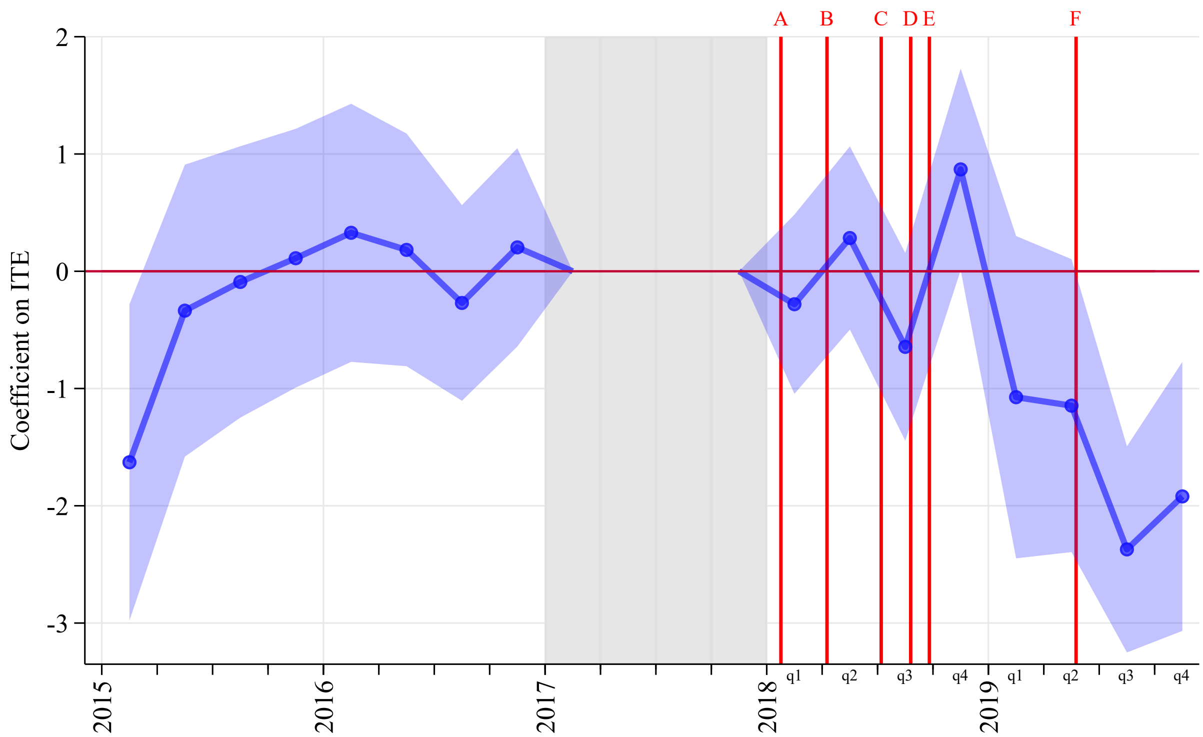
Figure 2: Deseasonalized U.S. Exports Controlling for Retaliatory Tariffs, 2015-2019



Notes: This figure plots a local polynomial through trade weighted means of residualized export values after controlling for retaliatory export tariffs and seasonality (country-product-calendar month effects) in Equation (19). The dashed horizontal line is the mean from 2015-2017 in the pre-trade war period. The vertical lines represent the different tariff waves: A (solar panels & washing machines, January 2018), B (metals, April-May 2018), C (China Wave 1, July 2018), D (China Wave 2, August 2018), E (China Wave 3 at 10%, September 2018), and F (China Wave 3 increase to 25%, May 2019).

Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

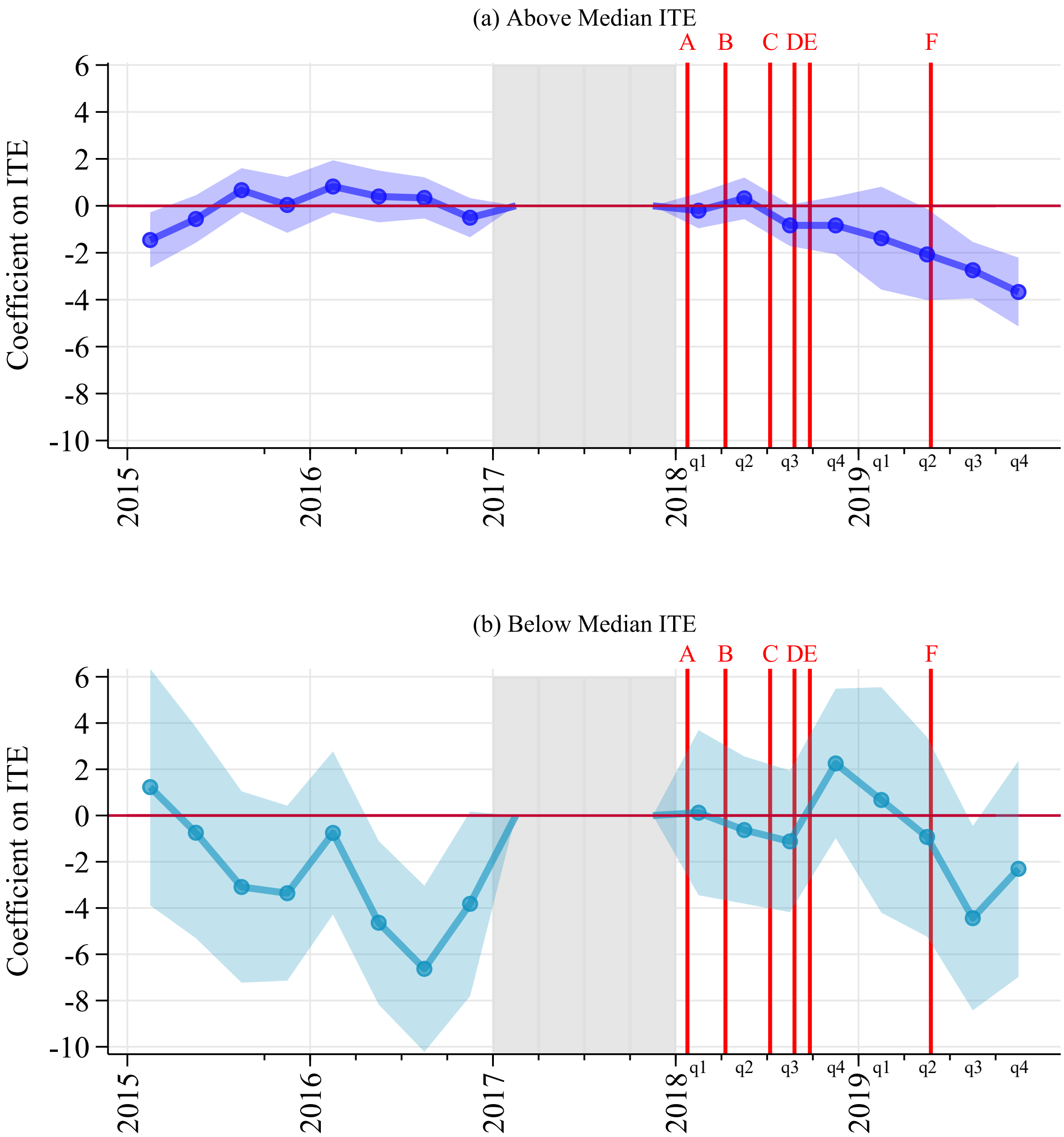
Figure 3: U.S. Exports and Exposure to 2018-2019 U.S. Import Tariffs, 2015Q1-2019Q4



Notes: This figure plots the coefficients (dots) and 95% CI (shaded band) on ITE_p from estimating Equation 21. The vertical lines represent the different tariff waves: A (solar panels & washing machines, January 2018), B (metals, April-May 2018), C (China Wave 1, July 2018), D (China Wave 2, August 2018), E (China Wave 3 at 10%, September 2018), and F (China Wave 3 increase to 25%, May 2019).

Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

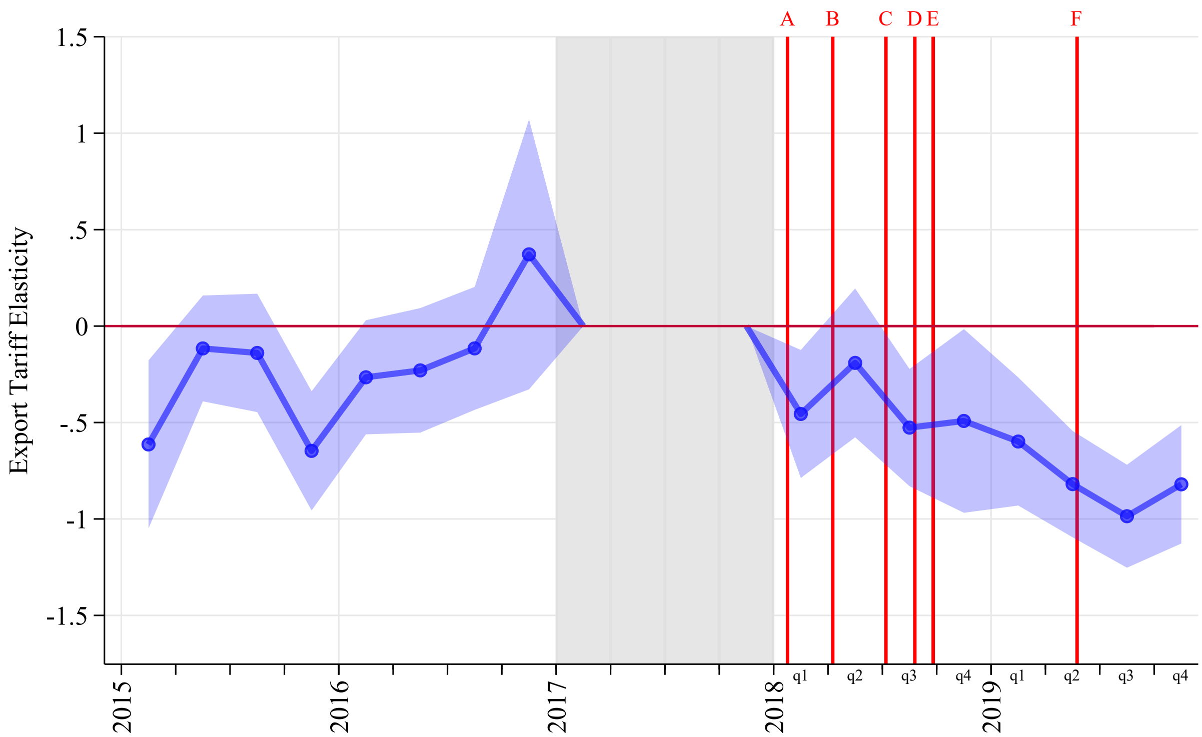
Figure 4: Event Study of High vs Low Exposure Products, 2015Q1-2019Q4



Notes: This figure plots the coefficients (dots) and 95% CI (shaded band) on ITE_p from estimating Equation 21 for products with above median (top panel) and below median (bottom panel) values of ITE_p. The vertical lines represent the different tariff waves: A (solar panels & washing machines, January 2018), B (metals, April-May 2018), C (China Wave 1, July 2018), D (China Wave 2, August 2018), E (China Wave 3 at 10%, September 2018), and F (China Wave 3 increase to 25%, May 2019).

Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

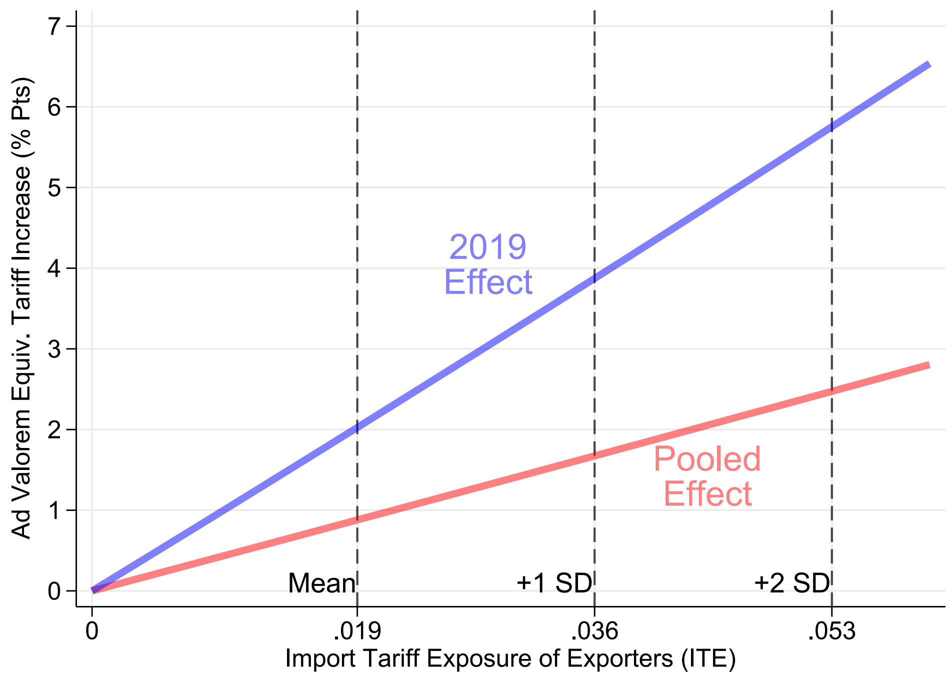
Figure 5: Event Study on Export Tariff Retaliation Elasticity Estimates, 2015Q1-2019Q4



Notes: This figure plots the coefficients (dots) and 95% CI (shaded band) on $ln(1+\tau_{pct})$ from estimating Equation 21. The vertical lines represent the different tariff waves: A (solar panels & washing machines, January 2018), B (metals, March-May 2018), C (China Wave 1, July 2018), D (China Wave 2, August 2018), E (China Wave 3 at 10%, May 2019), and F (China Wave 3 increase to 25%, September 2019).

Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Figure 6: *Ad Valorem* Equivalent Export Tariff from Import Tariff Exposure



Notes: This figure displays *ad valorem* equivalent tariffs (AVE) calculated with the coefficients for ITE_p and $ln(1 + \tau_{pct})$ in Column 1, Table 7 (pooled effect) and Column 1, Table 8 (2019 effect).
Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Table 1: Strategic Products: Localized vs. Source-Specific Vulnerabilities

Product	HHI_p^S	# Suppliers	HHI_p^C	# Sources
Machinery (HS2 85)	0.10	1,660	0.34	44
Batteries (HS4 8506/8507)	0.11	717	0.40	35
Semiconductors (HS4 8541/8542)	0.08	2,590	0.19	59
Chemicals (HS2 28)	0.27	58.5	0.44	13
Rare earths (HS4 2805/2846)	0.20	56	0.43	11
Pharmaceuticals (HS2 30)	0.31	222	0.42	23
Average (all HS6 products)	0.18	714	0.41	25
Compare to:				
Apparel not knitted (HS2 62)	0.04	2,603	0.30	63
Other textile (HS2 63)	0.04	1,040	0.46	46

Notes: The HHI_p measures are averages across HS6 categories within the specified product grouping. The count of suppliers and sources are weighted averages across HS6 categories within the specified product grouping, where the weights are imported value in 2017.
Source: Authors' calculations using 2017 LFTTD.

Table 2: Growth Rate Margins, 1993-2019

Margin	Growth Contribution (mean)	Share
Intensive Margin (Net Trade Creation)	2.7	0.41
Extensive Margin	4	0.59
(a) Net Add-Drop	2.2	0.34
(b) Net Entry-Exit	1.7	0.26
Total Growth	6.6	1.0

Source: Authors' calculations using 1992-2019 LFTTD.

Table 3: Breakdown of Import Growth by Margin

		Intensive Margin		Extensive Margin			
	Total Growth	*Trade Creation*	*Trade Destruction*	*ADD*	*DROP*	*ENTRY*	*EXIT*
$I(\Delta\tau_{pc} > 0) \times Post_t$	-0.17***	-0.02***	-0.05***	-0.01***	-0.02***	-0.02*	-0.04***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
F.E.	ct, pt, cp						
Obs.	956,000						

Source: Authors' calculations using 2013-2019 LFTTD.

Table 4: Breakdown of Import Growth by Margin and Supplier Concentration

		Intensive Margin		Extensive Margin			
	Total Growth	*Trade Creation*	*Trade Destruction*	*ADD*	*DROP*	*ENTRY*	*EXIT*
$I(\Delta\tau_{pc} > 0) \times Post_t$	-0.24***	-0.03***	-0.05***	-0.02***	-0.03***	-0.05***	-0.07***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$I(\Delta\tau_{pc} > 0) \times Post \times HHI_{p,t-1}$	0.50***	0.02	0.05**	0.05**	0.02	0.18***	0.20***
	(0.11)	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)
F.E.	ct, pt, cp						
Obs.	956,000						

Source: Authors' calculations using 2013-2019 LFTTD.

Table 5: Export Sectors that are the Most and Least Exposed to Import Tariffs

Panel A: Most Exposed

HS2	Product Description
84	Nuclear reactors, boilers, machinery and mechanical appliances
85	Electrical machinery and equipment and parts thereof
29	Organic chemicals
73	Articles of iron or steel
90	Optical, photographic, measuring, medical, surgical instruments

Panel B: Least Exposed

HS2	Product Description
78	Lead & articles thereof
80	Tin & articles thereof
67	Prepared feathers/down; artificial flowers; articles of human hair
06	Live trees & other plants
11	Products of milling; malt; starch; gluten

Notes: This table reports the five most and five least exposed HS2 product categories with respect to the 2018-2019 import tariffs. HS2 sectors are ranked by the share of HS6 products in each HS2 higher than the median ITE_p.
Source: Authors' calculations using 2016 LFTTD.

Table 6: Summary Statistics

	Mean	St. Dev.
Import Tariff Exposure		
ITE_p	0.019	0.017
ITE_p^{VC}	0.010	0.011
ITE_p^{T1}	8.4×10^{-6}	0.0001
ITE_p^{T2}	0.001	0.002
ITE_p^{T3}	0.019	0.017
ITE_p^{IMP}	0.037	0.043
ITE_p^{IO}	0.007	0.006
$\ln Exports_{pct}$	16.15	2.45
$\ln(1 + \tau_{pct})$	0.040	0.081

Notes: This table displays regression sample summary statistics weighted by country-product export values. Import tariff exposure measures and data described in Section 4.2.
Source: Authors' calculations using 2016 LFTTD.

Table 7: U.S. Exports and *Direct* Import Tariff Exposure

	(1)	(2)	(3)	(4)
	Weighted		Unweighted	Placebo
$\ln(1 + \tau_{pct})$	-1.425***	-0.500***	-0.636***	0.277
	(0.118)	(0.135)	(0.048)	(0.199)
$ITE_p \times I(> 2017Q4)$	-0.657***	-1.950***	-0.694***	
	(0.225)	(0.431)	(0.084)	
$ITE_p \times I(> 2015Q4)$				0.540*
				(0.301)
Country-HS6-Calendar Month	✓	✓	✓	✓
Country-HS2-Month	✓	-	✓	✓
Country-HS4-Month	-	✓	-	-
Observations	6,434,000	4,965,000	6,434,000	6,520,000

Notes: * p<10%; ** p<5%; *** p<1%. Robust standard errors in parentheses, clustered by HS6-calendar month. Calendar month (m) refers to 1, 2, 3,..., or 12. Observation counts rounded to comply with Census Bureau disclosure avoidance rules.
Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Table 8: **U.S. Exports and Import Tariff Exposure: Timing and Source of Effects**

	(1)	(2)	(3)	(4)	(5)	(6)
	By Year			Tranche	By Median of ITE_p	
	Weighted		Unweighted		Below	Above
$\ln(1+\tau_{pct})$	-1.423***	-0.487***	-0.635***	-1.424***	-1.141***	-1.260***
	(0.118)	(0.135)	(0.048)	(0.118)	(0.151)	(0.184)
$ITE_p \times I(2018)$	0.182	-0.749***	-0.498***			
	(0.231)	(0.285)	(0.089)			
$ITE_p \times I(2019)$	-1.502***	-3.159***	-0.897***			
	(0.3)	(0.656)	(0.104)			
$ITE_p^{T1} \times I(> 2017Q4)$				-17.98***		
				(6.73)		
$ITE_p^{T2} \times I(> 2017Q4)$				-1.471		
				(1.57)		
$ITE_p^{T3} \times I(> 2017Q4)$				-0.642***		
				(0.226)		
$ITE_p \times I(> 2017Q4)$					1.02	-1.402***
					(0.771)	(0.295)
Country-HS6-Calendar Month	✓	✓	✓	✓	✓	✓
Country-HS2-Month	✓	-	✓	✓	✓	✓
Country-HS4-Month	-	✓	-	-	-	-
Observations	6,434,000	4,965,000	6,434,000	6,434,000	3,164,000	3,141,000

Notes: * p<10%; ** p<5%; *** p<1%. Robust standard errors in parentheses, clustered by HS6-calendar month. Calendar month (m) refers to 1, 2, 3,..., or 12. Observation counts rounded to comply with Census Bureau disclosure avoidance rules.

Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Table 9: U.S. Exports and Import Tariff Exposure: Robustness

	(1) Baseline	(2) Including Payroll	(3) Drop China	(4) No Retaliation
$\ln(1+\tau_{pct})$	-1.425***	-1.424***	-0.698***	-0.480*
	(0.118)	(0.118)	(0.126)	(0.275)
$ITE_p \times I(> 2017Q4)$	-0.657***		-0.701***	-0.833***
	(0.225)		(0.203)	(0.233)
$ITE_p^{TVC} \times I(> 2017Q4)$		-1.511***		
		(0.308)		
Country-HS6-Calendar Month	✓	✓	✓	✓
Country-HS2-Month	✓	✓	✓	✓
Observations	6,434,000	6,434,000	6,273,000	6,223,000

Notes: * p<10%; ** p<5%; *** p<1%. Robust standard errors in parentheses, clustered by HS6-calendar month. Calendar month (m) refers to 1, 2, 3,..., or 12. Observation counts rounded to comply with Census Bureau disclosure avoidance rules.
Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Table 10: U.S. Exports and *Indirect* Import Tariff Exposure

	(1) Baseline	(2) +Importer ITE	(3) + IO ITE
$\ln(1+\tau_{pct})$	-1.425***	-1.428***	-1.428***
	(0.118)	(0.118)	(0.118)
$ITE_p \times I(> 2017Q4)$	-0.657***	-0.482**	-0.466*
	(0.225)	(0.232)	(0.246)
$ITE_p^{IMP} \times I(> 2017Q4)$		-0.254***	-0.256***
		(0.068)	(0.069)
$ITE_p^{IO} \times I(> 2017Q4)$			0.21
			(0.883)
Country-HS6-Calendar Month	✓	✓	✓
Country-HS2-Month	✓	✓	✓
Observations	6,434,000	6,434,000	6,434,000

Notes: * p<10%; ** p<5%; *** p<1%. Robust standard errors in parentheses, clustered by HS6-calendar month. Calendar month (m) refers to 1, 2, 3,..., or 12. Observation counts rounded to comply with Census Bureau disclosure avoidance rules.
Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Table 11: U.S. Exports and Import Tariff Exposure: Timing of Retaliatory Tariffs

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted		Weighted		Unweighted	
$\ln(1+\tau_{pct})$	-1.425***	-1.237***	-0.500***	-0.374**	-0.636***	-0.561***
	(0.118)	(0.132)	(0.135)	(0.150)	(0.048)	(0.052)
$\ln(1+\tau_{pct}) \times I(> 2017Q4)$		-0.215***		-0.139		-0.090***
		(0.07)		(0.090)		(0.025)
$ITE_p \times I(> 2017Q4)$	-0.657***	-0.687***	-1.950***	-1.946***	-0.694***	-0.683***
	(0.225)	(0.224)	(0.431)	(0.431)	(0.084)	(0.084)
Country-HS6-Calendar Month	✓	✓	✓	✓	✓	✓
Country-HS2-Month	✓	✓	-	-	✓	✓
Country-HS4-Month	-	-	✓	✓	-	-
Observations	6,434,000	6,434,000	4,965,000	4,965,000	6,434,000	6,434,000

Notes: * p<10%; ** p<5%; *** p<1%. Robust standard errors in parentheses, clustered by HS6-calendar month. Calendar month (m) refers to 1, 2, 3,..., or 12. Observation counts rounded to comply with Census Bureau disclosure avoidance rules.
Source: Authors' calculations using 2016 LFTTD and 2015–2019 public-use merchandise exports (U.S. Census Bureau, 2019).

Appendix

A Supply Chain Vulnerabilities

We define “friendly” countries to be countries with which the U.S. has a free trade agreement, in addition to countries of the European Union and Japan. The full list of trade partners is: Canada, Mexico, Iceland, Sweden, Denmark, United Kingdom, Ireland, Netherlands, Belgium, Luxembourg, France, Germany, Austria, Czech Republic, Hungary, Estonia, Latvia, Lithuania, Poland, Spain, Portugal, Italy, Australia, Colombia, Japan, South Korea, Chile, Peru, Panama, Israel, Jordan, and Costa Rica.

Table A-1: Localized Shocks: Key Products

Product	Supplier HHI	Supplier Ct (Mean)	Suppliers per Buyer
Machinery	0.10	1660	1.6
Batteries	0.11	717	1.3
Semiconductors	0.08	2590	1.7
Chemicals	0.27	58.5	1.1
Rare earths	0.20	56	1.3
Pharmaceuticals	0.31	222	1.6
Average (all products)	0.18	714	1.7
Compare to:			
Apparel not knitted	0.04	2603	2.5
Other textile	0.04	1040	1.8

Source: Authors’ calculations using 2017 LFTTD.

Table A-2: Source-Wide Shocks: Key Products

Product	Country HHI	Sources (Mean)	Friendly Share	China Share
Machinery	0.34	44	0.37	0.47
Batteries	0.40	35	0.64	0.26
Semiconductors	0.19	59	0.29	0.11
Chemicals	0.44	13	0.61	0.12
Rare Earths	0.43	11	0.42	0.50
Pharmaceuticals	0.42	23	0.75	0.02
Average (all products)	0.41	25	0.60	0.18
Compare to:				
Apparel not knitted	0.30	63	0.13	0.35
Other textile	0.46	46	0.10	0.47

Source: Authors' calculations using 2017 public-use merchandise exports (U.S. Census Bureau, 2019).

Table A-3: Localized Shocks: Medical Products

Product	Supplier HHI	Suppliers (Mean)	Suppliers per Buyer
Gloves & shields	0.01	34700	1.9
Goggles	0.02	2164	1.7
Masks	0.00	25910	2.2
Shoe covers	0.01	14810	1.8
Average (all products)	0.18	714	1.7

Source: Authors' calculations using 2017 LFTTD.

Table A-4: Source-Wide Shocks: Medical Products

Product	Country HHI	Sources (Mean)	Friendly Share	China Share
Gloves & shields	0.45	115	0.46	0.45
Goggles	0.33	48	0.12	0.54
Masks	0.55	123	0.16	0.73
Shoe covers	0.12	100	0.56	0.28
Average (all products)	0.41	25	0.60	0.18

Source: Authors' calculations using 2017 LFTTD.

B Export and Import Tariff Data

Monthly Export Data We use monthly, public-use U.S. export data provided by the U.S. Census Bureau from 2015 to 2019 (U.S. Census Bureau, 2019). This data spans a major revision of the HS nomenclature in 2017. To construct time consistent export flows at the 6-digit product level, we concord data from 2017-2019 back to the 2012 revision of the HS using concordances from the UN Statistics Division.

Our baseline sample excludes the products that undergo any merging or splitting of codes. Some 6-digit product codes from a prior revision may continue to be reused in subsequent revisions, but they might be aggregated or split in new ways. We keep track of the codes that undergo any revision where we have to aggregate for consistency.

Import Tariff Data We collected data at the 8-digit tariff line level on new tariffs levied by the U.S. from 2018-2019 as part of Sections 201, 232, and 301 investigations.

- Section 201: Solar Products, January 23, 2018. We use the list of products and country exemptions from Presidential Proclamation 9693 (Federal Register, Vol 83, p. 3541) of January 23, 2018.
- Section 201: Washing Machines, January 23, 2018. We use the list of products and country exemptions from Presidential Proclamation 9694 (Federal Register, Vol 83, p. 3553).
- Section 232: Steel and Aluminum, March 8, 2018 with subsequent waves adding or dropping countries (see Figure 2). These include the products listed in the Annexes to Presidential Proclamation 9704 (Federal Register, Vol. 83, p. 11619) and Presidential Proclamation 9705 (Federal Register, Vol. 83, p. 11625).
- Section 301: China, wave 1 (July 6, 2018), wave 2 (August 23, 2018), and wave 3 (September 24, 2018 and escalated on May 23, 2019). There are many modifications and changes, especially to wave 3, where products are added and removed from earlier annexes in a series of Federal Register notices. We use an official list provided by the USITC (`https://hts.usitc.gov/view/China%20Tariffs?release=2019HTSARev20`, accessed 1/30/2020).[28]

Export Tariffs and Retaliation Tariff Data Lists of new retaliatory tariffs levied against U.S. exports by various countries is gathered from destination country sources, following information produced for the trade war timeline in Bown and Kolb (2019). Since HS6 is the most dis-aggregated product category that is consistent across countries, we aggregate these lists to the HS 6-digit level. Tariffs are associated with the month in which they were imposed. The total amount of trade subject to retaliatory tariffs is computed using U.S. export data at the HS 6-digit level in 2017. We include the following retaliation actions:

[28] There are some duties levied at the HS 10-digit level against China, which we aggregated to the HS 8-digit level.

- Canada, July 2018: Retaliatory tariffs on $17.8 billion of U.S. exports. Information on the products facing retaliation ("June 29 list") accessed at https://www.piie.com/system/files/documents/bown-2018-07-05.xlsx.

- China, April 2018: Retaliatory tariffs on $2.4 billion of U.S. exports. Raw list of categories accessed at: http://images.mofcom.gov.cn/www/201803/20180326085959196.pdf, with additional information here: https://piie.com/system/files/documents/2018-04-09-piie-chart-lu-schott.xlsx.

- China, July 2018. Retaliatory tariffs on $29.2 billion of U.S. exports. Information on products facing retaliation ("Tariffs effective July 6") accessed at: https://www.piie.com/system/files/documents/bown-2018-06-22.xlsx

- China, August 2018. Retaliatory tariffs on $15.3 billion of U.S. exports. Information on products facing retaliation accessed at: http://images.mofcom.gov.cn/www/201808/20180808201049842.pdf.

- China, September 2019: Retaliatory tariffs on $51.3 billion of U.S. exports. Information on products facing retaliation accessed at: https://www.piie.com/system/files/documents/bown2018-09-20.zip.

- China, June 2019: Retaliatory tariffs on $39.8 billion of U.S. exports. Information on products facing retaliation ("China Tariff Rates", Column M) accessed at: https://www.piie.com/system/files/documents/bown-jung-zhang-2019-06-12.xlsx.

- European Union, June 2018: Retaliatory tariffs on $4.2 billion of U.S. exports. Information on the products facing "immediate retaliation" accessed at https://www.piie.com/system/files/documents/bown-2018-06-29.xlsx.

- India, June 2019: Retaliatory tariffs on $1.3 billion of U.S. exports. List of affected products accessed at https://docs.wto.org/dol2fe/Pages/FE_Search/FE_S_S009-DP.aspx?language=E&CatalogueIdList=246009,245254&CurrentCatalogueIdIndex=0&FullTextHash=371857150&HasEnglishRecord=True&HasFrenchRecord=True&HasSpanishRecord=True.

- Mexico, June 2018: Retaliatory tariffs on $4.5 billion of U.S. exports. Information on the products facing retaliation (group 2) accessed at http://www.dof.gob.mx/nota_detalle.php?codigo=5525036&fecha=05/06/2018.

- Turkey, May 2018: Retaliatory tariffs on $1.6 billion of U.S. exports. Information on the products facing retaliation accessed at https://docs.wto.org/dol2fe/Pages/FE_Search/FE_S_S009-DP.aspx?language=E&CatalogueIdList=245272&CurrentCatalogueIdIndex=0&FullTextHash=371857150&HasEnglishRecord=True&HasFrenchRecord=False&HasSpanishRecord=True.

- Turkey, August 2018: Retaliatory tariffs on $1.6 billion of U.S. exports. List is identical to May 2018 list, but rates are increased by different amounts. Information on the products facing retaliation accessed at https://www.resmigazete.gov.tr/eskiler/2018/08/20180815-6.pdf.

Because our export sample data goes back to 2015, we combine these retaliatory tariffs with the longer panel of destination-product export tariff data collected by Fajgelbaum et al. (2020) available from their replication package. As such, our measure of export tariffs combines the applied rate prior to the trade war and the increase from retaliation in 2018 and beyond, where applicable.

Input-Output Import Tariff Exposure Construction We construct a HS6 product measure of exposure, ITE_p^{IO}, incorporating exporters' potential import tariff exposure through input-output linkages. Since, economy-wide I-O linkages are only available at a more aggregated industry level, we rely on a set of concordances between HS6 product p and IO industry j.[29]

Input usage ($prod_{jk}$) and total cost ($prod_j$ and $comp_j$) of each industry is obtained from the most recent Use Table, 2012, of the detailed input-output accounting tables published by the U.S. Bureau of Economic Analysis (BEA). These tables show the "use" in dollars of inputs that each U.S. industry purchases (domestic or imports) from all other industries. To maintain coherence between BEA I-O methodology, we calculate the implied duty share faced by each industry, $\frac{duties_k}{imports_k}$, using public-use annual merchandise imports in 2016. The BEA input-output tables are designed to capture linkages between an output industry's use of goods and services inputs from suppliers. This requires that we assign each imported good to the industry that would have produced the product rather than the industry code of the actual importer of record, which might be a retailer, wholesaler, or other services firm in the LFTTD. Nevertheless, the firm-level linkages between exporters and industries are recovered when we apportion the IO exposure measure to disaggregated 6-digit product exports, which would not be feasible without the information in LFTTD.

We concord HS6 imported products across the 405 BEA IO industry codes in two steps. First, we match every HS6 product to a 4-digit NAICS (HS-NAICS) using a 2016 import value trade weight. In the public-use import data, 92% of imports match to a manufacturing NAICS code (31-33), 4% to mining, utilities and construction (21-23), and 3% to agriculture (11) with the residual to public administration. Second, we concord the more aggregated BEA IO industry codes to each of the 4-digit NAICS codes (IO-NAICS).[30]

Now we assign an IO based import tariff exposure to an exported HS6 product p according to exporter industry codes j we observe in data. The share of product p in industry j's exports, $\frac{exports_{pj}}{exports_j}$, is calculated by aggregating firm level exports. For each exporting firm in 2016, we assign a 4-digit NAICS representing the predominant industry of firm i, which we define as the industry with highest employment across the firm's establishments. Using the IO-NAICS concordance we can assign each firm IO duty share as in equation (13). To map these into products, we take a weighted average using export values of all the firms that export product p. The mapping of an exported product p to an IO industry j thus

[29] Construction of firm-level IO tables is outside the scope of this paper especially given well-documented challenges in U.S. data of allocating firm level imports across multiple sectors for multi-unit, multi-activity firms that dominate goods trade (Feenstra and Jensen, 2012).

[30] We are grateful to Abdul Munasib for sharing the concordance between NAICS and BEA IO industries used in Helper and Munaisb (2022).

relies on confidential firm level data. The main advantage of this approach, compared to using the public-use HS-NAICS concordance, is that the HS6 mappings are based on firms' actual export patterns and can accommodate common situations where firms in multiple different NAICS industries all export the same product (violating assumptions used in unique concordances).