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ABSTRACT

We investigate the phenomenon of trade re-allocations across countries as a result of the U.S.-China trade war. Using quarterly data on U.S. imports, we find evidence, as do others, of trade diversion in a range of industries and products, including products not targeted by U.S. tariffs on China. We are however the first to ask what seems to drive these trade reallocation activities. First, we show that they seem to be driven by differences in comparative advantage across countries: countries with a greater revealed comparative advantage in a product benefit (in terms of exports to the U.S.) more from U.S. tariffs on China. Second, we show that there is evidence of spillovers to similar non-targeted products: products in similar industries (as defined by their HS codes) are also similarly affected. This is consistent with the colocation effects. Third, our findings also suggest that bystander countries with greater capital abundance are more heavily impacted in capital-intensive industries, suggesting that a higher proportion of more flexible or transferable assets provides flexibility to alter production to respond to new trade opportunities. Finally, we show that the countries that export more to the U.S. as a result of the tariffs on China also export more to other countries. This suggests that firms are entering these countries and once there, export not just to the U.S. but everywhere.

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1 Introduction

Global trade experienced an unprecedented shock when two major economic powers, the United States and China, decided to engage in a head-on trade war with each other in early 2018. Most studies on the topic have focused on the impact of the trade war on the U.S. and China themselves. A smaller body of literature (to which this paper belongs) has documented patterns of substantial global trade re-allocations as a result of this event. Most prominently, (Nicita, 2019; Fajgelbaum et al., 2023), have found that trade was diverted towards a number of bystander countries (i.e. countries other than the U.S. and China) including Mexico, the European Union and Vietnam. They provide ample evidence of the trade war’s spillover effects.

Our paper contributes to this growing body of literature by exploring the *mechanisms* through which trade is diverted towards these bystander countries. We use quarterly data on detailed product-level imports at the eight-digit Harmonized System (HS) code level into the U.S. from 30 countries from January 2016 to May 2019, as well as United Nations (UN) Comtrade data. We uncover a number of new patterns. First, we show that not only is there significant diversion towards other countries, but that the pattern of diversion follows revealed comparative advantage. We find that countries with a greater revealed comparative advantage in a product are able to export more to the US as a result of the tariffs on China.¹ Moreover, this is more so when a product is intensive in the country’s abundant factor. Second, we find that there seem to be positive spillover effects on products that are similar in terms of being in the same 4-digit Standard Industrial Classification (SIC) codes to those on which tariffs are imposed. We attribute these co-location effects to production externalities across related products. Third, our results could help explain the mixed results found in the literature to date regarding trade diversion to other countries. For example, Cigna et al. (2022) do not find significant evidence of trade diversion towards third countries, though they do find a strong negative relationship between U.S. tariffs and U.S. imports from China. In contrast, Nicita (2019) and Fajgelbaum et al. (2023) find strong evidence of such diversion. Fajgelbaum et al. (2023) find that the pattern of this diversion is heterogeneous across countries. In response to U.S. tariffs on China, some countries (Mexico) export more to the U.S. and more to the rest of the world (ROW) while others (Canada) export more to the U.S. and less to the ROW. Some countries export less to the U.S. and more to the ROW (Turkey), while a few export less to both the U.S. and ROW (Sweden). The same kind of heterogeneity is found in terms of responses to Chinese tariffs on the U.S. As far as

¹This makes economic sense: countries that have costs that make them un-competitive are not likely to be able to take advantage of the opportunities created by US tariffs on China.

the heterogeneous response of countries goes, they suggest that countries with higher foreign direct investment (FDI) stock and a larger share of exports covered by trade agreements responded with stronger export growth as a result of the trade wars.

The trade war between the U.S. and China has already generated a large literature. As might be expected, it has been found to have negative effects on both the U.S. and China. Flaaen et al. (2020) looks into the trade war’s effect on the price of two particular products: washers and dryers. They found that in response to the 2018 tariffs, the price of washers, which are subject to tariffs, increased by 12 percent while the price of dryers, not subject to tariffs, also increased by the same amount. They attribute this to the complementarities between washers and dryers.² They emphasize the difference in the effects of tariffs on a small subset of exporting countries (which allows firms to avoid the tariffs by relocation to non-targeted countries) and tariffs on all imports where such measures are not useful.

Jiao et al. (2021) go one step further to look into firm-level responses to the trade war. They use transaction-level export and firm-level domestic sales data with all exporting firms coming from a single Chinese prefecture from January 2017 to April 2019 to examine Chinese exporters’ responses to U.S. tariffs in terms of price and sales. They find that Chinese exporters reduce exports to the U.S. but are able to fully make up for the loss by exporting to the rest of the world. They found that the surges in U.S. tariffs on Chinese exports did not affect the price of Chinese exports. Rather, these tariffs have had a redistributive effect on the exporting pattern of Chinese producers: while their exports to the U.S. have notably declined, they have exported more to the ROW. Their finding of the lack of change in FOB³ prices is in line with the findings of complete pass-through of tariff rates on U.S. consumers that have been shown in Amiti et al. (2020), Cavallo et al. (2021) and Fajgelbaum et al. (2020).

There are a number of reasons why we might see (or mistakenly think we see) complete pass-through. First, if products were homogeneous and transport costs non-existent, the only effect of a tariff on a single trading partner (as opposed to one imposed on all trading partners) would be to reallocate exports globally (even without firms relocating production) and leave FOB prices and the level of trade with the world unaffected. However, existing estimates of elasticities between goods that come from different countries are far from infinite, see for example, Fajgelbaum et al. (2020). As a consequence, one would expect the usual effect on world prices of Chinese exports hit by a tariff: namely that they fall.

Second, we might see what looks like complete pass-through due to mis-measurement of prices for a given quality. Suppose tariffs raise quality, and hence price, but this quality

²However, they do not provide a formal model.

³Free on Board.

increase is not accounted for. Then it is possible for unit values to remain unchanged, while price adjusted for quality upgrading falls. A problem with this argument comes from the fact that the tariffs imposed during the trade war were ad-valorem in nature. Simple theory, see for example Falvey (1979), predicts that while specific tariffs would raise quality, ad-valorem ones would not.

Finally, it could be that there is heterogeneity in the response of prices: the world price of some goods may fall, while that of others may fall by little or even rise. Amiti et al. (2022) make such an argument. They suggest that this pattern is driven by trade in the large number of products that make up a small fraction of the value of trade. Goods with large trade values tend to show the expected pattern: namely falling FOB prices.

Benguria et al. (2022) also use firm-level data to explore the impact of the trade war on Chinese firms' performance. They find that the trade war has raised the level of trade policy uncertainty measured using textual analysis of listed firms' annual reports. They document a negative relationship between measured firm-level trade policy uncertainty and firm performance in terms of firm-level investment, R&D expenditures and profits.

Huang et al. (2019) use data on firm's stock prices to look at the impact of global supply chain disruptions due to the trade war. They find that U.S. firms' indirect exposure to trade with China via domestic supply chains has an economically larger negative effect on their stock market performance than their direct trade exposure does.

Reallocation and redistribution effects of the trade war at a more aggregate level, i.e., in terms of employment across counties and sectors within the U.S. and China are also studied. Flaaen and Pierce (2019) look at employment reallocation across sectors within the U.S.; Waugh (2019) looks at U.S. county-level employment in response to retaliatory tariffs imposed by China retaliation. Chor and Li (2021) consider the spatial impact of the trade war by examining changes in nightlight intensity against regional exposure to tariffs, and their findings also suggest significant heterogeneities in impacts across geographical locations in China.

Grossman et al. (2021) provide the theoretical framework for analyzing changes to global supply chains in response to tariffs. Other studies have also used general equilibrium or computable general equilibrium (CGE) models to estimate the reallocation effects of the trade war. Devarajan et al. (2021) develop a multi-country, multi-sector computable general equilibrium (CGE) model of global trade to explore how developing countries should respond to the U.S.-China trade war. Their findings suggest that there would be a significant reallocation of trade in favor of developing countries through mostly the channel of trade diversion in response to the tariff spikes between the U.S. and China, so developing countries would be able to reap substantial gains without having to resort to any action. Bolt et al.

(2019) confirm this trade diversion effect via an extended multi-regional, general equilibrium model (EAGLE) to explore consequences from the scenarios of U.S. tariffs into China and Chinese tariffs into the U.S. They found that despite a contraction in global output, third parties, or the European Union in this case, stand to benefit from this trade war. Balistreri et al. (2018) also use a multi-regional, multi-sector general-equilibrium model to analyze the effects of the bilateral tariffs and found similar results: while the trade war would be costly for both the U.S. and China, other regions e.g. Europe, stand to gain from the diversion effect. In addition, they find that at the industry level, there are winners and losers within the U.S. itself e.g. steel and some manufacturing industries would gain while agriculture, motor vehicle, and services would lose in terms of income for factors of production and land.

Fajgelbaum et al. (2023) examine how third countries react to the U.S.-China trade war. They find that in response to U.S. tariffs on China, many bystander countries export more not only to the U.S. but also to the ROW. They rationalize the result with a downward-sloping supply curve. All other combinations of responses (export more to the U.S. and less to the ROW, less to the U.S. and more to the ROW and less to both) are also present for at least some bystander countries. Some of the heterogeneity in response across countries is due to countries with higher FDI stocks and a larger share of exports covered by trade agreements responding with stronger export growth as a result of the trade war. In all their analyses, they assume a *common response* across all goods to tariffs. This finding makes sense in a Melitz-type model with free entry. A tariff on China by the U.S. shifts up the ex-ante expected profits in competitor countries, and more so for those countries with a comparative advantage in the good. This would raise entry. These new firms would export not just to the U.S., but to other profitable countries as found by Fajgelbaum et al. (2023). Alviarez et al. (2023) argue that markups⁴ reflect oligopoly and oligopsony forces, with relative bargaining power as weights. They argue that such power is endemic in U.S. trade given GVCs⁵ and the fixed costs involved in their formation. A model is able to account for these forces allows for the observed complete pass through and makes predictions relating buyer and seller market power that are borne out in the data.

Bekkers and Schroeter (2020) use both empirical analyses and simulations to demonstrate the trade diversion effect for other countries and the costliness of the trade war for both the U.S. and China. Nicita (2019) find that although the U.S. tariffs on China resulted in a decline of 25 percent in the volume of imports of the tariffed products, other countries including Taiwan, Mexico, the European Union, and Vietnam have been able to benefit. They also found preliminary evidence that Chinese firms absorb part of the cost of the tariffs

⁴The degree to which products are priced over their marginal costs.

⁵Global value chains.

by lowering their export prices. Mao and Görg (2020) estimate the impact of the trade war on bystander countries via global supply chains, i.e. the way tariffs affect the imports of intermediate goods to the U.S. from China and consequently the import of final goods made from those intermediate goods from the U.S. to third countries. Via this channel, they find that bystander countries such as the EU, Canada, and Mexico also suffer from losses in absolute terms due to increased U.S. tariffs on Chinese goods.

The remainder of our paper is organized as follows. Section 2 presents the overall patterns of the changes in U.S. imports from China and the ROW in both targeted and non-targeted products. Section 3 presents the empirical framework for our analyses as well as our empirical findings. Section 4 explores the potential underlying mechanisms of the diversion effects. Section 5 concludes.

2 Overall Patterns

We first document some patterns derived from the publicly available monthly administrative U.S. import data from the U.S. Census Bureau⁶ that record values and quantities of trade flows at the HS-10 digit level. We aggregate the data to HS-8 quarterly level, which is the level of analysis we mainly use for products in our regressions. The patterns demonstrate significant diversion effects in terms of trade flows in both targeted and non-targeted products between countries. Targeted products are defined as products subject to the US’ tariffs against China and non-targeted products are the ones not subject to these tariffs. These broad patterns help provide context to our subsequent empirical framework and analyses.

Industries are categorized into 18 categories as listed in Table 1. Product codes following the HS are also grouped into relevant industries according to the same classifications in subsequent analyses.⁷

Table 2 presents the total number of products, number of products targeted during the trade war as well as the breakdown of targeted products by the level of the tariff (15% or 25%) imposed on China by the U.S. in 2018 and 2019 respectively.

⁶These data can be accessed at <https://usatrade.census.gov/>.

⁷The 18th category “Works of Art, Collectors’ Pieces and Antiques” only accounts for a tiny fraction of the observations so we exclude it from our analyses.

Table 1: The Industry List

Industry	Explanation
1	Processed Food
2	Mineral Products
3	Products of the Chemical or Allied Industries
4	Raw Hides and Skins, Leather, Furskins and Articles Thereof; Saddlery and Harness; Travel Goods, Handbags and Similar Containers; Articles of Animal Gut (Other Than Silkworm Gut)
5	Plastics and Articles Thereof Rubber and Articles Thereof
6	Wood and Articles of Wood;
7	Textile
8	Apparel and Textile Articles
9	Footwear, Headgear, Umbrellas, Sun Umbrellas, Walking Sticks, Seatsticks, Whips, Riding-Crops and Parts Thereof; Prepared Feathers and Articles Made Therewith; Artificial Flowers; Articles of Human Hair
10	Articles of Stone, Plaster, Cement, Asbestos, Mica or Similar Materials; Ceramic Products; Glass and Glassware; Natural or Cultured Pearls, Precious or Semiprecious Stones, Precious Metals, Metals Clad With Precious Metal, and Articles Thereof; Imitation Jewelry; Coin
11	Base Metals and Articles of Base Metal
12	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof
13	Electrical machinery and equipment and parts thereof
14	Vehicles, Aircraft, Vessels and Associated Transport Equipment
15	Optical, Photographic, Cinematographic, Measuring, Checking, Precision, Medical or Surgical Instruments and Apparatus; Clocks and Watches; Musical Instruments; Parts and Accessories Thereof
16	Furniture
17	Toys, games and sports requisites; parts and accessories thereof; Miscellaneous manufactured articles
18	Works of Art, Collectors' Pieces and Antiques

Table 2: Tariff During the U.S.-China Trade War

Industry	Total HS 8-digit # Products	Year = 2018				Year = 2019			
		# Targeted	# Non-Targeted		# Targeted	# Non-Targeted		Tariff 15% 25%	# Non-Targeted
			Tariff 15% 25%	#		Tariff 15% 25%	#		
1	790	330	330 0	460	788	457 331	2		
2	204	160	157 3	44	170	13 157	34		
3	1804	1304	1298 6	500	1469	171 1298	335		
4	376	325	177 148	51	224	47 177	152		
5	231	186	186 0	45	228	42 186	3		
6	574	513	513 0	61	574	58 516	0		
7	935	917	917 0	18	935	18 917	0		
8	746	0	0 0	746	745	745 0	1		
9	197	28	28 0	169	197	169 28	0		
10	422	274	273 1	148	421	148 273	1		
11	988	501	493 8	487	930	437 493	58		
12	797	644	196 448	153	344	148 196	453		
13	586	435	213 222	151	363	150 213	223		
14	272	251	135 116	21	152	17 135	120		
15	423	226	81 145	197	244	163 81	179		
16	91	77	77 0	14	89	12 77	2		
17	204	24	24 0	180	204	180 24	0		
18	7	0	0 0	7	7	7 0	0		

Figure 1 shows the impact of the U.S.-China trade war on the U.S. *aggregate import value* by industry. For each industry, we calculate the difference of the (log) import value of all targeted products between the first half of 2018 and the first half of 2019 and arrange them in the corresponding columns. The last column shows the same statistic for all non-targeted products. It can be seen that there was a significant overall increase in the import values of non-targeted products while the import values of most targeted products fell. The figure suggests that the tariff surges between the U.S. and China indeed reduced the total value of import from China by the US.

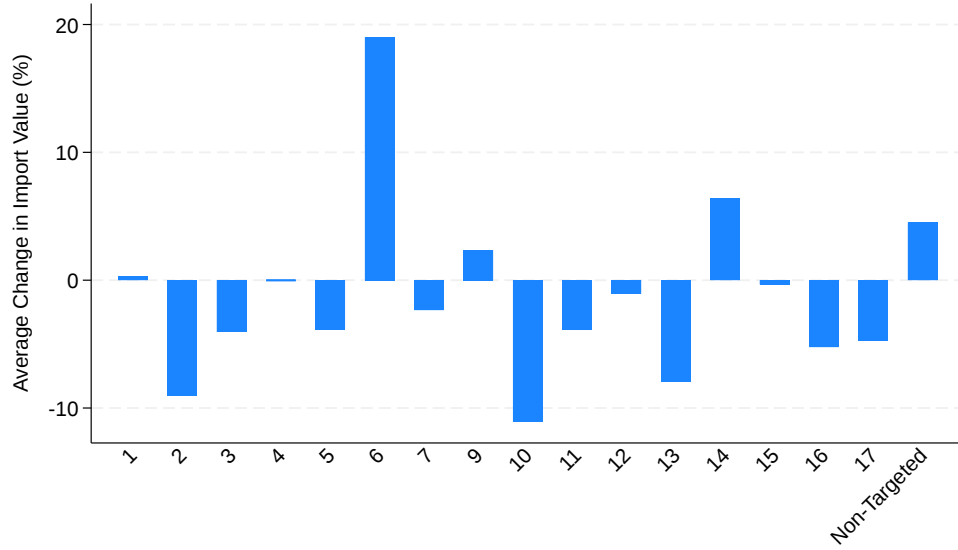


Figure 1: Changes in Total U.S. Imports between First Half of 2019 and First Half of 2018

Figure 2 explores the potential trade diversion effects of the trade war. It depicts the values of targeted products in each industry (first 17 columns) and all non-targeted products (last column) that the U.S. imported between the first six months of 2019 and the first six months of 2018 from China in dark blue. Note that this difference is always negative reflecting the fall in imports from China over this period. The change in imports from the ROW in each product in the corresponding periods is depicted in light blue. Note that these are usually positive. In other words, the U.S. saw a huge reduction in the targeted imports from China accompanied by a smaller increase in the targeted imports from the ROW in this period, which indicates trade diversion. In Categories 6, 9, and 14, total U.S. imports actually rose as imports from the ROW rose by more than imports from China fell as is evident in Figure 1. The U.S. also imported more from the ROW in non-targeted products - suggesting that the trade war had spillover effects on non-targeted products.

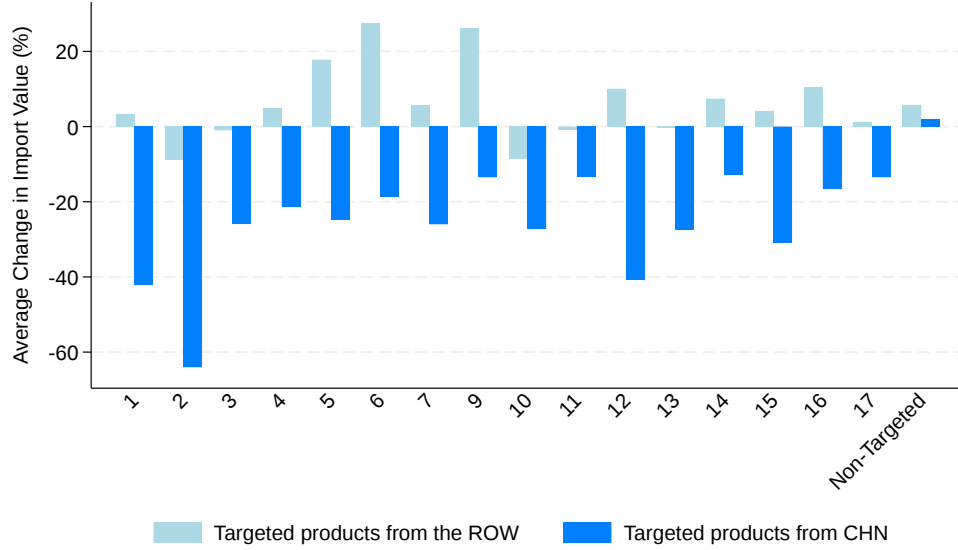
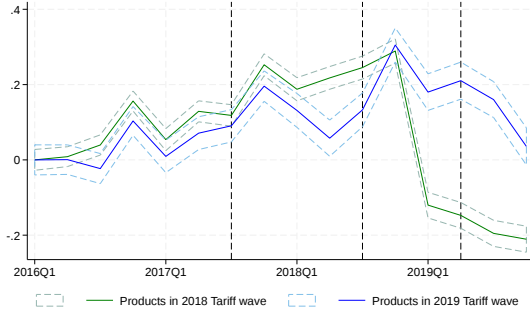


Figure 2: Changes in US Imports from China and ROW between First Half of 2019 and First Half of 2018

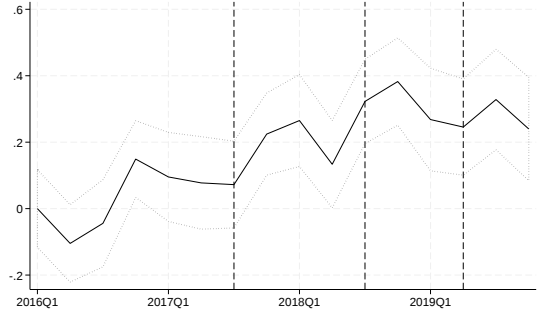
We then explore the variation of these diversion effects over time by performing a simple regression of the log of U.S. imports in a given category of product (targeted vs. non-targeted) from a given country (China vs. ROW) on four different dummy variables over time. These dummy variables represent targeted products from China, non-targeted products from China, targeted products from ROW, and non-targeted products from ROW respectively. Country-product fixed effects and product-quarter fixed effects (which control for seasonal adjustment) are included. The values of the coefficients on the four dummy variables over time are depicted in Figure 3 below.

These coefficients represent the difference in U.S. imports of the corresponding product category from the corresponding country and the rest of the products in a given time period where a time period is a quarter. For example, panel (a) shows that U.S. imports from China of products targeted by the U.S. in the 2018 tariff wave (in green) fell sharply (by almost 40 percent) in the last quarter of 2018. We also identify important milestones of the trade war on the graph over time: The first vertical dashed line marks the start of the Office of the United States Trade Representative's (USTR) investigation of China's economic practices; the second one indicates the start of the tariff in 2018, while the third one indicates the start of the tariff in 2019.

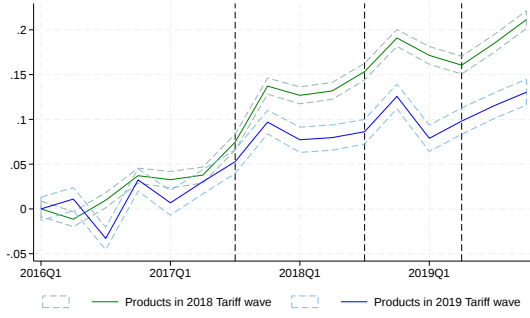
Figure 3: The Trend of U.S. Imports from China



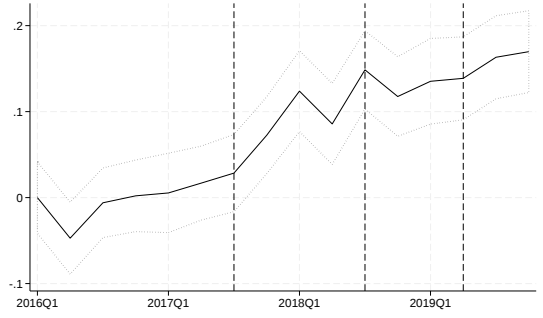
(a) U.S. Imports from China: The Targeted Products



(b) U.S. Imports from China: The non-Targeted Products



(c) U.S. Imports from the ROW: The Targeted Products



(d) U.S. Imports from the ROW: The Non-Targeted Products

The graphs above give us a sense of the effects around these critical timeline milestones for both targeted products and non-targeted products. For China, there was an episode of reduction in its exports to the U.S. of the targeted products in August 2017 (when the investigation happened) before another episode of more dramatic reduction following the beginning of the trade war. The reverse patterns are observed for the rest of the world: there are marked increases in their exports of the targeted products to the U.S. after both of these events. These patterns also hold for non-targeted products albeit less dramatically, suggesting the spillovers of the impact of the tariff surges over to non-targeted products as well.

3 Trade Diversion Effects on Targeted and Non-Targeted Products

This section explores, more formally, the impact of the tariffs on U.S. imports from China and the rest of the world for both targeted products and non-targeted products using U.S.

import data and UN Comtrade quarterly data. We obtain significant and robust results confirming the spillover effects of the trade war to third countries on both targeted and non-targeted products as observed in Section 2. Our findings are robust to the inclusion of time trends and when we break down diversion effects by major trade partners of the U.S.

3.1 Diversion Effects on Targeted Products

In exploring the effects of the tariff surges on the value of U.S. imports from bystander countries, our identification strategy relies on a difference-in-difference estimation as in equation (1) below where the dependent variable is the log of imports of product j from country c at time t .

$$\begin{aligned} \log(Imports)_{jct} = & \beta_{1,Event} Targeted_{jc}^{China} \times d_{tar} + \beta_{3,Event} Targeted_{jc}^{ROW} \times d_{tar} \\ & + \mu_{1,jc} + \mu_{2,j,qr} + \mu_{3,ct} + \varepsilon_{jct} \end{aligned} \quad (1)$$

In the specification above, $Targeted_{jc}^{China}$ is an indicator equal to one if the product is targeted by U.S. tariffs against China and is imported from China. A product is defined as targeted if a tariff was imposed on it at any time during the time period of the trade war. As a result, this status of being “targeted” is binary and time-invariant. $Targeted_{jc}^{ROW}$ is an indicator equal to one if the product is targeted by U.S. tariffs against China and is imported from the ROW. d_{tar} is a time indicator equal to one when the tariff is in place for product j . $\mu_{1,jc}$ represents country-product fixed effects. $\mu_{2,j,qr}$ defines product-quarter fixed effects which controls for the seasonal adjustment, while $\mu_{3,ct}$ represents country-time fixed effects.

The coefficients of interest are $\beta_{1,Event}$ and $\beta_{3,Event}$. The former (latter) shows the difference in U.S. import value between targeted and non-targeted products from China (the ROW) when a tariff on China is in place.

The results of the estimation of equation 1 are presented in column (1) of Table 3. These give the impact of U.S.-China tariffs on U.S. imports from China and the ROW. U.S. imports of targeted products from China fall by about 26% relative to non-targeted products. U.S. imports of targeted products from ROW increased by about 4% relative to non-targeted products during this time period as shown by the estimate of $\beta_{3,Event}$ in the first column.

3.2 Diversion Effects on Both Targeted and Non-Targeted Products

As clearly indicated in Figure 3 of Section 2, both targeted and non-targeted products are affected by the U.S.-China trade war. Therefore, in addition to quantifying the impact of the trade war on the difference between targeted and non-targeted products in terms of U.S. import value, it is worth exploring the trade war's diversion effects on non-targeted products while allowing for time trends. Since a non-targeted product is defined as one that was not subject to U.S.' tariffs against China during the trade war period - its non-targeted status is binary and time-invariant in the same way as the targeted product. We estimate equation 2 below:

$$\begin{aligned}
\log(Imports)_{jct} = & \beta_{1,Event} Targeted_{jc}^{China} \times d_{tar} + \beta_{2,Event} NonTargeted_{jc}^{China} \times D_{tar} \\
& + \beta_{3,Event} Targeted_{jc}^{ROW} \times d_{tar} + \beta_{4,Event} NonTargeted_{jc}^{ROW} \times D_{tar} \\
& + \gamma_1 Targeted_{jc}^{China} \times t + \gamma_2 NonTargeted_{jc}^{China} \times t \\
& + \gamma_3 Targeted_{jc}^{ROW} \times t + \gamma_4 NonTargeted_{jc}^{ROW} \times t \\
& + \mu_{1,jc} + \mu_{2,j,qr} + \varepsilon_{jct}
\end{aligned} \tag{2}$$

The specification above has the same variables as in equation (1). For example, d_{tar} is a dummy for the period during which tariffs were imposed on China and $Targeted_{jc}^{China}$ is a dummy which is one if product j is imported from China and is targeted. In addition, we have the interaction between the indicator variable for non-targeted products imported from China, denoted by $NonTargeted_{jc}^{China}$, with the tariff event, D_{tar} dummy, where D_{tar} takes the value of 1 for any time from Quarter 4 of 2018 and after and 0 for other time periods. Analogous to this we have the interaction of D_{tar} and $NonTargeted_{jc}^{ROW}$ which is a dummy for the product being not targeted and the imports to the U.S. coming from the ROW. Separate linear time trends are also allowed for imports of targeted products from China and the ROW in the targeted and non-targeted products. $\mu_{1,jc}$ represents country-product fixed effects and $\mu_{2,j,qr}$ are product-quarter fixed effects which controls for the seasonal adjustment.

Column (2) of Table 3 presents the estimation results for equation 2. After controlling for the linear time trend, we can see that U.S. imports of non-targeted products from China increase by 5.9% (based on the estimate of $\beta_{2,Event}$) while imports from the ROW increase by 3.4% (based on the estimate of $\beta_{4,Event}$) during the trade dispute.

The increase in the value of U.S. imports of Chinese non-targeted products may indicate that Chinese firms curb loss in the targeted products by expanding the markets of non-targeted products. The fact that exporters in a third country increase their exports of

non-targeted products is consistent with *colocation effects*. That is, exporters (who tend to be large multi-product producers) expand their market share of non-targeted products by sharing market penetration efforts across different products. We explore this colocation effect in more detail in Section 4.3.

3.3 Diversion Effects Before vs. After August 2017

Figure 3 in Section 2 also suggests that the impact of the U.S.-China trade war appeared as soon as the start of the USTR investigation in August 2017. Therefore, we divide the pre-tariff period into two parts: before August 2017 versus after August 2017, and estimate equation 3 as follows to explore whether this investigation had any impact on global trade activities:

$$\begin{aligned}
\log(Imports)_{jct} = & \beta_{1,Inv}Targeted_{jc}^{China} \times d_{Inv} + \beta_{1,Event}Targeted_{jc}^{China} \times d_{tar} \\
& + \beta_{2,Inv}NonTargeted_{jc}^{China} \times D_{Inv} + \beta_{2,Event}NonTargeted_{jc}^{China} \times D_{tar} \\
& + \beta_{3,Inv}Targeted_{jc}^{ROW} \times d_{Inv} + \beta_{3,Event}Targeted_{jc}^{ROW} \times d_{tar} \\
& + \beta_{4,Inv}NonTargeted_{jc}^{ROW} \times D_{Inv} + \beta_{4,Event}NonTargeted_{jc}^{ROW} \times D_{tar} \\
& + \gamma_1 Targeted_{jc}^{China} \times t + \gamma_2 NonTargeted_{jc}^{China} \times t \\
& + \gamma_3 Targeted_{jc}^{ROW} \times t + \gamma_4 NonTargeted_{jc}^{ROW} \times t \\
& + \mu_{1,jc} + \mu_{2,j,qr} + \varepsilon_{jct}
\end{aligned} \tag{3}$$

Specification 3 essentially repeats equation 2 with the addition of the interaction terms between the targeted/non-targeted product status indicator variables with the indicator variables for the period during the investigation but before the initiation of the tariffs. d_{Inv} takes the value of 1 if the time falls into the time period after the investigation started and before a tariff was imposed on product j , and 0 otherwise. D_{Inv} takes the value of 1 if the time falls into the specific investigation of between Quarter 4 of 2017 and Quarter 2 of 2018, and 0 otherwise. As before, d_{tar} is a dummy for the period during which the tariff was imposed on product j , and D_{tar} takes the value of 1 for any time from Quarter 4 of 2018 and after and 0 for other time periods.

Column (3) of Table 3 presents the estimates for equation 3 above. The coefficients $\beta_{1,Inv}$, $\beta_{2,Inv}$ and $\beta_{3,Inv}$, $\beta_{4,Inv}$ are highly significant and positive, suggesting that U.S. imports of both targeted and non-targeted products from China and ROW increased sharply after the start of the investigation in August 2017 even before the tariffs were enforced: specifically, U.S. imports of targeted products from China increased by 16% ($\beta_{1,Inv}$) and those from ROW

increased by 8.7% ($\beta_{3,Inv}$) on average. Meanwhile, U.S. imports of non-targeted products from China increased by 13% ($\beta_{2,Inv}$), and those from ROW increased by a smaller amount (5%, corresponding to $\beta_{4,Inv}$) on average. This might reflect an increase in imports both from China and elsewhere in anticipation of the tariffs.

Table 3: Trade Diversion

	(1)	(2)	(3)
$\beta_{1,Inv}Targeted_{jc}^{China} \times d_{Inv}$			0.16*** (0.010)
$\beta_{1,Event}Targeted_{jc}^{China} \times d_{tar}$	-0.26*** (0.02)	-0.24*** (0.01)	-0.065*** (0.02)
$\beta_{2,Inv}NonTargeted_{jc}^{China} \times D_{Inv}$			0.13*** (0.03)
$\beta_{2,Event}NonTargeted_{jc}^{China} \times D_{tar}$		0.059* (0.03)	0.19*** (0.04)
$\beta_{3,Inv}Targeted_{jc}^{ROW} \times d_{Inv}$			0.087*** (0.003)
$\beta_{3,Event}Targeted_{jc}^{ROW} \times d_{tar}$	0.040*** (0.005)	0.037*** (0.003)	0.13*** (0.005)
$\beta_{4,Inv}NonTargeted_{jc}^{ROW} \times D_{Inv}$			0.050*** (0.01)
$\beta_{4,Event}NonTargeted_{jc}^{ROW} \times D_{tar}$		0.034*** (0.01)	0.082*** (0.02)
$\gamma_1Targeted_{jc}^{China} \times t$		0.0049*** (0.0010)	-0.0076*** (0.001)
$\gamma_2NonTargeted_{jc}^{China} \times t$		0.0075*** (0.0003)	0.0072** (0.003)
$\gamma_3Targeted_{jc}^{ROW} \times t$		0.017*** (0.003)	0.00060* (0.0004)
$\gamma_4NonTargeted_{jc}^{ROW} \times t$		0.0055*** (0.001)	0.0019 (0.001)
Cons	12.1*** (0.0009)	12.0*** (0.002)	12.0*** (0.003)
Country-HS8 FE	Yes	Yes	Yes
HS8-Quarter FE	Yes	Yes	Yes
Country-Time FE	Yes	No	No
R-sq	0.874	0.873	0.873
N	2561868	2561870	2561870

3.4 Diversion Effects Across Major Trade Partners by Industry

In this section, we explore the heterogeneous diversion effects across the U.S.' major trade partners and industries using U.S. import data from USITC. As we look at trade diversion, we look only at how imports of products (or groups of products) from the ROW as a whole, or from particular countries in the ROW, to the U.S. are affected.

We first explore how trade diversion effects vary across 18 different industries specified

in Table 1. We run the same specification as in equation 1 for different industries. The results, presented in Panel 1 in Table 4, show that the US imports from China decreased in most industries except Industries 8, 9, 11 and 17, while the imports from ROW increased consistently across almost all industries.

We then further decompose the trade diversion effects across industries into individual impacts on the U.S.' major trade partners. We follow a similar procedure as in equation 1 but interact with country dummies. The estimates are presented in Panel 2 in Table 4. We can see that the EU, ASEAN countries and Mexico seem more heavily affected by the U.S.-China trade war. The fact that ASEAN countries are more affected is in line with the idea that their comparative advantages are closer to that of China, making their goods and services close substitutes for Chinese products.

Table 4: Trade Diversion by Country and Industry

Industry	1	2	3	4	5	6	7	8	9	
Panel 1: Trade Diversion to the ROW										
China	-0.41*** (0.06)	-0.35*** (0.1)	-0.33*** (0.03)	-0.35*** (0.06)	-0.26*** (0.08)	-0.20*** (0.05)	-0.22*** (0.04)	0.038 (0.03)	0.053 (0.06)	
The ROW	0.088*** (0.02)	0.21*** (0.05)	0.14*** (0.02)	0.13*** (0.02)	0.18*** (0.03)	0.13*** (0.02)	0.12*** (0.02)	0.10*** (0.02)	0.14*** (0.04)	
Panel 2: Decompose the ROW into Major Trading Partners Separately										
EU	0.11*** (0.03)	0.11 (0.08)	0.12*** (0.02)	0.13*** (0.03)	0.21*** (0.05)	0.10*** (0.04)	0.12*** (0.03)	0.099*** (0.02)	0.16*** (0.05)	
ASEAN	0.094* (0.05)	-0.36 (0.3)	0.25*** (0.07)	0.23*** (0.06)	0.49*** (0.1)	0.41*** (0.07)	0.23*** (0.07)	0.12*** (0.05)	0.26** (0.1)	
Canada	-0.055 (0.08)	0.38*** (0.1)	0.036 (0.06)	0.0045 (0.07)	-0.032 (0.1)	0.15* (0.08)	0.20** (0.09)	0.076 (0.08)	-0.16 (0.2)	
Mexico	0.12 (0.08)	0.29 (0.3)	0.18*** (0.07)	0.13 (0.1)	0.056 (0.2)	0.16 (0.1)	-0.0051 (0.09)	-0.21** (0.09)	0.11 (0.2)	
Japan	0.013 (0.07)	0.28 (0.3)	0.15*** (0.05)	0.14** (0.07)	-0.30* (0.2)	0.10 (0.09)	0.041 (0.06)	0.14* (0.07)	0.49*** (0.2)	
Korea	0.028 (0.08)	0.22 (0.2)	0.27*** (0.08)	0.16** (0.08)	-0.066 (0.2)	0.10 (0.1)	0.11 (0.09)	0.028 (0.10)	0.38* (0.2)	
Taiwan	0.013 (0.09)	-0.32 (0.4)	0.14* (0.08)	-0.021 (0.09)	0.12 (0.2)	0.012 (0.10)	0.16* (0.08)	0.22** (0.1)	0.030 (0.2)	
Others	0.091*** (0.03)	0.32*** (0.09)	0.15*** (0.03)	0.12*** (0.04)	0.11** (0.05)	0.056 (0.04)	0.12*** (0.03)	0.12*** (0.02)	0.075 (0.06)	
Industry	10	11	12	13	14	15	16	17	18	Non-Targeted
Panel 1: Trade Diversion to the ROW										
China	-0.23*** (0.05)	-0.014 (0.04)	-0.35*** (0.04)	-0.43*** (0.04)	-0.14** (0.06)	-0.28*** (0.05)	-0.28*** (0.06)	-0.011 (0.05)	-0.66*** (0.2)	0.059* (0.03)
The ROW	0.087*** (0.02)	0.20*** (0.01)	0.11*** (0.01)	0.11*** (0.01)	0.17*** (0.03)	0.11*** (0.02)	0.018 (0.03)	0.100*** (0.04)	0.071 (0.09)	0.081*** (0.02)
Panel 2: Decompose the ROW into Major Trading Partners Separately										
EU	0.099*** (0.03)	0.21*** (0.02)	0.13*** (0.02)	0.12*** (0.02)	0.12*** (0.04)	0.077*** (0.02)	-0.055 (0.04)	0.025 (0.06)	0.26** (0.1)	0.033* (0.02)
ASEAN	0.15** (0.07)	0.21*** (0.05)	0.14*** (0.04)	0.15*** (0.04)	0.20** (0.09)	0.16*** (0.06)	0.33*** (0.09)	0.12 (0.09)	0.049 (0.3)	0.16*** (0.04)
Canada	-0.036 (0.09)	0.19*** (0.05)	0.091** (0.04)	-0.016 (0.07)	0.22** (0.1)	0.042 (0.08)	0.012 (0.1)	0.22 (0.2)	0.36 (0.3)	-0.0063 (0.05)
Mexico	0.064 (0.09)	0.24*** (0.06)	0.17** (0.07)	0.13* (0.08)	0.36*** (0.1)	-0.031 (0.1)	0.062 (0.1)	-0.28* (0.2)	-0.11 (0.7)	0.031 (0.06)
Japan	0.0011 (0.10)	0.26*** (0.06)	0.0040 (0.05)	0.023 (0.06)	0.027 (0.1)	0.16** (0.07)	-0.025 (0.2)	0.012 (0.1)	0.15 (0.2)	0.029 (0.05)
Korea	0.18 (0.1)	0.39*** (0.07)	0.19*** (0.07)	0.21*** (0.07)	0.21* (0.1)	0.14 (0.1)	-0.17 (0.2)	0.21 (0.1)	1.01* (0.6)	-0.019 (0.06)
Taiwan	0.31** (0.1)	0.12** (0.05)	0.16*** (0.05)	0.13** (0.06)	0.18 (0.1)	0.18** (0.08)	-0.19 (0.2)	0.25** (0.1)	0.33 (0.4)	-0.040 (0.05)
Others	0.057 (0.04)	0.14*** (0.03)	0.062** (0.02)	0.081*** (0.03)	0.24*** (0.06)	0.13*** (0.04)	0.014 (0.06)	0.22*** (0.08)	-0.11 (0.1)	0.0099 (0.02)

4 Underlying Mechanisms of Trade Diversion Effects

In this section, we explore three potential mechanisms that could be driving the results above:

(i) revealed comparative advantage (RCA), (ii) capital intensity and capital abundance, and (iii) colocation effects. The first two are applicable to both targeted and non-targeted products while the colocation effect channel is relevant only for non-targeted products.

4.1 Revealed Comparative Advantage (RCA)

In exploring whether countries with greater revealed comparative advantage in a product benefit more from the U.S.-China trade war (i.e. by exporting more to the U.S.), we estimate the following equation:

$$\begin{aligned}
\log(Imports)_{jct} = & \beta_{1,Event} Targeted_j \times d_{tar} + \beta_{2,Event} Targeted_j \times d_{tar} \times \log(RCA)_{jc} \\
& + \beta_{3,Event} NonTargeted_j \times D_{tar} + \beta_{4,Event} NonTargeted_j \times D_{tar} \times \log(RCA)_{jc} \\
& + \gamma_1 Targeted_j \times t + \gamma_2 Nontargeted_j \times t \\
& + \mu_{1,jc} + \mu_{2,j,qr} + \varepsilon_{jct}
\end{aligned} \tag{4}$$

In equation 4 above, the coefficients of interest are $\beta_{2,Event}$ and $\beta_{4,Event}$, which captures how the level of revealed comparative advantage interacts with trade diversion. We expect that countries with a greater RCA in a product will be well situated and more able to step into the breach, i.e., we expect the response to be greater when RCA is higher. Time trend variables are included to control for time trends. Product-country and product-time fixed effects are included as in other specifications. $\log(RCA)_{jc}$ is the log of revealed comparative advantage of product j and country c . As before, d_{tar} is a dummy for the period during which the tariff was imposed on product j , and D_{tar} takes the value of 1 for any time from Quarter 4 of 2018 and after and 0 for other time periods.

Using UNCTAD STAT database for comparative advantage ⁸, we calculate the average RCA over time for product j of country c from 2015 to 2017 to get a measure that reflects the overall level of RCA by country and product.

Column (1) in Table 5 presents the estimates for equation 4 above. The results confirm that trade diversion is governed by the level of RCA: both $\beta_{2,Event}$ and $\beta_{4,Event}$ are significant and positive, suggesting that the higher the level of RCA, the greater the positive impact of the trade war on U.S. imports of a product from that country. In Table 5, we focus on the import flow from the ROW only.

As we are also interested in exploring the role of RCA in the trade diversion that happened after the start of the investigation on China in August 2017 and before the tariff was put in place, we add interaction terms with d_{Inv} which is the dummy variable for this time period as in equation 3 and estimate the extended equation as follows:

⁸Data downloaded from https://unctadstat.unctad.org/wds/ReportFolders/reportFolders.aspx?sCS_referer=&sCS_ChosenLang=en

$$\begin{aligned}
\log(Imports)_{jct} = & \beta_{1,Inv}Targeted_j \times d_{Inv} + \beta_{2,Inv}Targeted_j \times d_{Inv} \times \log(RCA)_{jc} \\
& + \beta_{1,Event}Targeted_j \times d_{tar} + \beta_{2,Event}Targeted_j \times d_{tar} \times \log(RCA)_{jc} \\
& + \beta_{3,Inv}NonTargeted_j \times D_{Inv} + \beta_{4,Inv}NonTargeted_j \times D_{Inv} \times \log(RCA)_{jc} \\
& + \beta_{3,Event}NonTargeted_j \times D_{tar} + \beta_{4,Event}NonTargeted_j \times D_{tar} \times \log(RCA)_{jc} \\
& + \gamma_1Targeted_j \times t + \gamma_2Nontargeted_j \times t \\
& + \mu_{1,jc} + \mu_{2,j,qr} + \varepsilon_{jct}
\end{aligned} \tag{5}$$

As before, d_{tar} is a dummy for the period during which the tariff was imposed on product j , and D_{tar} takes the value of 1 for any time from Quarter 4 of 2018 and after and 0 for other time periods.

Estimates are presented in column (2) in Table 5, which basically confirm that the spillovers to the ROW are greater when there is more RCA. Just as the least disadvantaged minority students are most able to take advantage of affirmative action, countries that have high RCA in a product are more likely to fill the breach.

Table 5: Trade Diversion and RCA

	(1)	(2)
$\beta_{1,Inv}Targeted_j \times d_{Inv}$		0.089*** (0.003)
$\beta_{2,Inv}Targeted_j \times d_{Inv} \times \log(RCA)_c$		0.012*** (0.001)
$\beta_{1,Event}Targeted_j \times d_{tar}$	0.041*** (0.002)	0.13*** (0.004)
$\beta_{2,Event}Targeted_j \times d_{Inv} \times \log(RCA)_c$	0.010*** (0.001)	0.014*** (0.001)
$\beta_{3,Inv}NonTargeted_j \times D_{Inv}$		0.053*** (0.01)
$\beta_{4,Inv}NonTargeted_j \times D_{Inv} \times \log(RCA)_c$		0.012** (0.005)
$\beta_{3,Event}NonTargeted_j \times D_{tar}$	0.043*** (0.009)	0.090*** (0.01)
$\beta_{4,Event}NonTargeted_j \times D_{tar} \times \log(RCA)_c$	0.020*** (0.004)	0.024*** (0.005)
$\gamma_1 Time \times \mathbb{1}\{Target = 1\}$	0.0075*** (0.0002)	0.00069** (0.0003)
$\gamma_2 Time \times \mathbb{1}\{Target = 0\}$	0.0055*** (0.0007)	0.0020** (0.0010)
Cons	11.8*** (0.002)	11.9*** (0.002)
Country-HS8 FE	Yes	Yes
HS8-Quarter FE	Yes	Yes
R-sq	0.866	0.866
N	2417184	2417184

4.2 Capital Intensity and Capital Abundance

In exploring whether the level of capital intensity and capital abundance play a role in how much bystander countries benefit from the U.S.-China trade war, we estimate the following equation:

$$\begin{aligned}
\log(Imports)_{jct} = & \beta_1 Targeted_j \times d_{tar} \\
& + \beta_2 Targeted_j \times d_{tar} \times \log(KInt)_j + \beta_3 Targeted_j \times d_{tar} \times \log K_abund_c \\
& + \beta_4 Targeted_j \times d_{tar} \times \log(KInt)_j \times \log K_abund_c \\
& + \beta_5 NonTargeted_j \times D_{tar} \\
& + \beta_6 NonTargeted_j \times D_{tar} \times \log(KInt)_j + \beta_7 NonTargeted_j \times D_{tar} \times \log K_abund_c \\
& + \beta_8 NonTargeted_j \times D_{tar} \times \log(KInt)_j \times \log K_abund_c \\
& + \gamma_1 Targeted_j \times t + \gamma_2 NonTargeted_j \times t + \mu_{1,jc} + \mu_{2,j,qr} + \varepsilon_{jct}
\end{aligned} \tag{6}$$

In equation 6 above, $\log(KInt)_j$ represents the log of the level of capital intensity of product j ; $\log K_abund_c$ represents the log of capital abundance of country c . To calculate capital abundance of each country, we divided capital endowment by population. The regression extends on our baseline equations presented in earlier sections by including a number of interaction terms between the targeted product status and event dummies as well as log of capital intensity of the product in question and log of capital abundance. Our coefficient of interest is β_4 , which shows the channel via which RCA operates. If it is via the Heckscher Ohlin channel, the effects on imports which are capital intensive should be larger if the country is capital abundant. In other words, we expect As before, d_{tar} is a dummy for the period during which the tariff was imposed on product j , D_{tar} takes the value of 1 for any time from Quarter 4 of 2018 and after, and 0 for other time periods, $\mu_{1,jc}$ represents country-product fixed effects and $\mu_{2,j,qr}$ are product-quarter fixed effects that controls for the seasonal adjustment.

The data on capital intensity was downloaded from the NBER database.⁹ We took the average at the country level for the latest three years which are from 2011 to 2013. The data source for the level of capital endowment is the World Bank’s World Integrated Trade Solution database.¹⁰ To calculate capital abundance of each country, we divided capital endowment by population. We also took the average of capital abundance for each country over the latest three years available from 2014 to 2016. Averaging out the measure across these years helps minimize the effects of potential outliers in the data.

Table 6 presents the regression results for equation 6. As we can see, β_4 is positive and significant at the 5% level, suggesting that when a tariff is imposed on China, the spillover effect to third countries vary: they are larger for countries that are capital-abundant if the product is capital-intensive. These results confirm that factor abundance and intensity are a channel that affect the extent of spillovers from the U.S.-China trade war.

⁹<https://www.nber.org/research/data/nber-ces-manufacturing-industry-database>

¹⁰https://wits.worldbank.org/trade_outcomes.html (Section on “Export Portfolio and Factor Endowments”)

Table 6: Trade Diversion and Factor Abundance

	(1)
$\beta_1 Targeted_j \times d_{tar}$	0.52*** (0.06)
$\beta_2 Targeted_j \times d_{tar} \times \log(KInt)_c$	-0.22*** (0.06)
$\beta_3 Targeted_j \times d_{tar} \times \log K_abund_c$	-0.045*** (0.005)
$\beta_4 Targeted_j \times d_{tar} \times \log(KInt)_c \times \log K_abund_c$	0.014** (0.005)
$\beta_5 NonTargeted_j \times D_{tar}$	1.05*** (0.2)
$\beta_6 NonTargeted_j \times D_{tar} \times \log(KInt)_c$	0.33 (0.2)
$\beta_7 NonTargeted_j \times D_{tar} \times \log K_endow_c$	-0.091*** (0.02)
$\beta_8 NonTargeted_j \times D_{tar} \times \log(KInt)_c \times \log K_endow_c$	-0.033 (0.02)
$\gamma_1 Time \times \mathbb{1}\{Target = 1\}$	0.0078*** (0.0003)
$\gamma_2 Time \times \mathbb{1}\{Target = 0\}$	0.0061*** (0.001)
Cons	11.8***
Country-HS8 FE	Yes
HS8-Quarter FE	Yes
	(0.003)
R-sq	0.867
N	2221329

4.3 Colocation Effects

In this section, we explore colocation effects as a potential mechanism underlying the impact of the US-China trade war. These effects lead to a kind of “spillover” on closely related products defined as those falling within the same HS code. To illustrate, consider HS code 852580 which includes television cameras, digital cameras, and video camera recorders. Within this HS code, the U.S. has imposed tariffs on specific subcategories (85258030, 85258040, and 85258050) imported from China. These subcategories are referred to as targeted products. Meanwhile, the other subcategories (85258010 and 85258020) within the same HS code 852580, which are not subject to U.S. tariffs, are categorized as non-targeted products. Interestingly, these non-targeted products (85258010 and 85258020) closely resemble the targeted products (85258030, 85258040, and 85258050), often sharing segments of the production line or being manufactured by the same multiproduct firms. The channel of colocation effects centers on the way the export performance of targeted products from a third country influences its exports of non-targeted products to both the U.S. and ROW.

A plausible mechanism behind these colocation effects revolves around the market pen-

etration strategies employed by multiproduct firms. In essence, as these firms expand into foreign markets, various functions like distribution systems and advertising campaigns tend to unify across their entire product lines. Consequently, any trade diversion among targeted products could subsequently impact the exports of non-targeted products by bystander countries.

In exploring colocation effects as a potential driver of trade diversion, we leverage the notion that colocation effects should be more pronounced if imports of related targeted products witness substantial growth in the US market. As the related targeted goods gain traction, companies are inclined to invest more in advertising campaigns, distribution networks, and other factors. Consequently, this enhanced effort extends to non-targeted products that share similarities with the targeted ones. Thus, non-targeted products exhibiting greater resemblance to the targeted items are also expected to benefit more from the colocation effect.¹¹

More specifically, we confine our sample to imports of non-targeted products from the ROW. Products similar to a given targeted product can be identified based on their HS category. We propose different definitions of similar products to the targeted product. Products in the same HS6 code are most likely to be similar, though products in the same HS4 code are also similar, but less so, while products in the same HS2 code are even less similar on average to the given targeted product. The more similar the product, the more likely it is to be produced by multiproduct firms and the more likely are co-location effects. $\Delta \log(Imp)$ represents the increase in the US imports of targeted products similar to the given non-targeted one. Similarity is defined at the HS2, HS4 and HS6, level respectively. We divide the period into 4 sections. (1) before 2017Q3; (2) 2017Q4 - 2018Q2: the start of the investigation; (3) 2018Q3-2019Q2: the 2018 wave of tariffs; (4) 2019Q3 - 2019Q4 the 2019 wave of tariffs and estimate the following equation:

¹¹One potential alternative approach to investigate the effects of colocation that we considered involves taking advantage of the varying timing of tariff implementation on targeted goods. Specifically, we would create a binary variable for each non-targeted HS-8-digit product and this variable would switch to 1 if a closely related product (one sharing the same first 6 HS digits) becomes subject to tariffs. Subsequently, the regression analysis would have the log of imports of a non-targeted product on the left hand side, and the binary variable just described together with relevant fixed effects on the right hand side.

This method would allow us to examine the divergent trends between non-targeted products within a 6-digit HS code, differentiating those related to targeted products within the same 6-digit HS codes. Moreover, by exploiting the varying tariff implementation timelines for targeted products, we can isolate the colocation effects while accounting for unobservable product-level shocks. Unfortunately, this approach faces limitations in cases where tariff imposition within 6-digit HS codes is substantially correlated. For instance, during the initial tariff wave (2018Q3), around 93% of 6-digit HS codes either remained tariff-free or were uniformly subject to US tariffs on Chinese imports across their respective 8-digit HS codes. As a result, meaningful identification rests on only the remaining 7% of 6-digit HS codes, where diverse timings of tariff impact on different 8-digit HS codes of non-targeted products occur due to their association with targeted goods. As such, we opt for the identification strategy elaborated in the main text.

$$\begin{aligned}
\log(Imports)_{jct} = & \beta_1 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\} \\
& + \beta_2 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\} \\
& + \beta_3 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\} \\
& + \beta_4 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\} \times \Delta \log(Imp) \\
& + \beta_5 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\} \times \Delta \log(Imp) \\
& + \beta_6 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\} \times \Delta \log(Imp) \\
& + \gamma_1 Time_t + \mu_{1,jc} + \mu_{2,j,qr} + \varepsilon_{jct}
\end{aligned} \tag{7}$$

Regression results are presented in Table 7. We get robustly and highly significant and positive results for β_5 and β_6 , which are the coefficients on the interaction terms indicating colocation effects within either HS2, HS4 or HS6 product codes and from both the 2018 and the 2019 waves of tariffs, confirming the presence of highly significant colocation effects in the spillovers of the trade war. The fact that β_4 is insignificant supports our argument that colocation effects only started to take place after firms expanded their market share in a targeted product from the first wave of tariffs.

Table 7: The Impact on the Non-Targeted Products

	(1) HS2	(2) HS4	(3) HS6
$\beta_1 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\}$	0.051*** (0.01)	0.045*** (0.02)	0.019 (0.02)
$\beta_2 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\}$	0.048*** (0.01)	0.056*** (0.02)	0.037 (0.03)
$\beta_3 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\}$	0.068*** (0.02)	0.097*** (0.02)	0.11*** (0.04)
$\beta_4 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\} \times \Delta \log(Imp)$	0.057 (0.03)	0.017 (0.02)	0.0037 (0.03)
$\beta_5 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\} \times \Delta \log(Imp)$	0.12*** (0.03)	0.064*** (0.02)	0.039* (0.02)
$\beta_6 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\} \times \Delta \log(Imp)$	0.34*** (0.04)	0.14*** (0.02)	0.077*** (0.03)
$\gamma_1 Time$	0.0012 (0.001)	0.00030 (0.002)	-0.0031 (0.003)
Cons	11.7*** (0.01)	11.6*** (0.01)	11.2*** (0.02)
Country-HS8 FE	Yes	Yes	Yes
HS8-Quarter FE	Yes	Yes	Yes
R-sq	0.849	0.847	0.830
N	170345	115651	49826

We also explore how these colocation effects interact with (i) the share of targeted products within each HS code at the 2-digit, 4-digit and 6-digit levels, and (ii) the level of RCA by including relevant interaction terms as shown in Table 8. We measure the share of targeted products within HS2 (or HS4 or HS6) in third countries as: $X = \text{Ratio of Targeted Products to Total Products in 2016 before the start of trade disputes}$. Results in Table 8 confirm both the roles of RCA and size of targeted products in magnifying colocation effects: the larger the size of the targeted products (meaning a relatively higher level of importance of the product), and the higher the comparative advantage, the larger impact on the non-targeted but similar products.

Table 8: The Impact on the Non-Targeted Products with Interaction

	(1)		(2)		(3)		(4)		(5)		(6)	
	$X = \text{Size of Targeted Products}$						$X = \log(RCA)$					
	HS2	HS4	HS4	HS6	HS2	HS4	HS2	HS4	HS2	HS4	HS6	HS6
$\beta_1 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\}$	0.043*** (0.01)	0.033* (0.02)	0.031 (0.03)	0.031 (0.03)	0.051*** (0.01)	0.047*** (0.02)	0.051*** (0.01)	0.047*** (0.02)	0.051*** (0.01)	0.047*** (0.02)	0.021 (0.02)	0.021 (0.02)
$\beta_2 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\}$	0.039** (0.02)	0.069*** (0.02)	0.067** (0.03)	0.067** (0.03)	0.045*** (0.02)	0.058*** (0.02)	0.045*** (0.02)	0.058*** (0.02)	0.045*** (0.02)	0.058*** (0.02)	0.042 (0.03)	0.042 (0.03)
$\beta_3 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\}$	0.068*** (0.02)	0.13*** (0.03)	0.14*** (0.04)	0.14*** (0.04)	0.071*** (0.02)	0.11*** (0.03)	0.071*** (0.02)	0.11*** (0.03)	0.071*** (0.02)	0.11*** (0.03)	0.12*** (0.04)	0.12*** (0.04)
$\beta_4 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\} \times \Delta \log(Imp)$	0.086** (0.04)	0.024 (0.03)	0.031 (0.03)	0.031 (0.03)	0.077* (0.04)	0.017 (0.02)	0.077* (0.04)	0.017 (0.02)	0.077* (0.04)	0.017 (0.02)	0.012 (0.03)	0.012 (0.03)
$\beta_5 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\} \times \Delta \log(Imp)$	0.15*** (0.04)	0.091*** (0.03)	0.079*** (0.03)	0.079*** (0.03)	0.16*** (0.04)	0.063*** (0.02)	0.16*** (0.04)	0.063*** (0.02)	0.16*** (0.04)	0.063*** (0.02)	0.045* (0.03)	0.045* (0.03)
$\beta_6 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\} \times \Delta \log(Imp)$	0.42*** (0.05)	0.16*** (0.03)	0.12*** (0.04)	0.12*** (0.04)	0.38*** (0.05)	0.14*** (0.03)	0.38*** (0.05)	0.14*** (0.03)	0.38*** (0.05)	0.14*** (0.03)	0.083*** (0.03)	0.083*** (0.03)
$\beta_7 \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\} \times X$	-0.019 (0.02)	-0.014 (0.01)	0.012 (0.01)	0.012 (0.01)	0.0053 (0.009)	0.0078 (0.01)	0.0053 (0.009)	0.0078 (0.01)	0.0053 (0.009)	0.0078 (0.01)	0.015 (0.02)	0.015 (0.02)
$\beta_8 \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\} \times X$	-0.023 (0.02)	0.017 (0.01)	0.033*** (0.01)	0.033*** (0.01)	0.00028 (0.009)	0.0067 (0.01)	0.00028 (0.009)	0.0067 (0.01)	0.00028 (0.009)	0.0067 (0.01)	0.025 (0.02)	0.025 (0.02)
$\beta_9 \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\} \times X$	0.011 (0.02)	0.045*** (0.01)	0.035** (0.01)	0.035** (0.01)	0.017 (0.01)	0.032** (0.01)	0.017 (0.01)	0.032** (0.01)	0.017 (0.01)	0.032** (0.01)	0.052*** (0.02)	0.052*** (0.02)
$\beta_{10} \mathbb{1}\{2017Q4 \leq t \leq 2018Q2\} \times \Delta \log(Imp) \times X$	0.030 (0.03)	0.0054 (0.01)	0.018 (0.02)	0.018 (0.02)	0.036 (0.02)	0.0031 (0.02)	0.036 (0.02)	0.0031 (0.02)	0.036 (0.02)	0.0031 (0.02)	0.028 (0.02)	0.028 (0.02)
$\beta_{11} \mathbb{1}\{2018Q3 \leq t \leq 2019Q2\} \times \Delta \log(Imp) \times X$	0.031 (0.02)	0.020 (0.01)	0.026** (0.01)	0.026** (0.01)	0.053** (0.02)	0.00084 (0.02)	0.053** (0.02)	0.00084 (0.02)	0.053** (0.02)	0.00084 (0.02)	0.023 (0.02)	0.023 (0.02)
$\beta_{12} \mathbb{1}\{2019Q3 \leq t \leq 2019Q4\} \times \Delta \log(Imp) \times X$	0.087*** (0.02)	0.013 (0.02)	0.031* (0.02)	0.031* (0.02)	0.078*** (0.03)	-0.0018 (0.02)	0.078*** (0.03)	-0.0018 (0.02)	0.078*** (0.03)	-0.0018 (0.02)	0.028 (0.03)	0.028 (0.03)
$\gamma_1 Time$	0.0012 (0.001)	0.00033 (0.002)	-0.0029 (0.003)	-0.0029 (0.003)	0.0012 (0.001)	0.00030 (0.002)	0.0012 (0.001)	0.00030 (0.002)	0.0012 (0.001)	0.00030 (0.002)	-0.0030 (0.003)	-0.0030 (0.003)
Cons	11.7*** (0.01)	11.6*** (0.01)	11.2*** (0.02)	11.2*** (0.02)	11.7*** (0.01)	11.6*** (0.01)	11.7*** (0.01)	11.6*** (0.01)	11.7*** (0.01)	11.6*** (0.01)	11.2*** (0.02)	11.2*** (0.02)
R-sq	0.849	0.847	0.830	0.830	0.849	0.847	0.849	0.847	0.849	0.847	0.830	0.830
N	170345	115651	49826	49826	170331	115651	170331	115651	170331	115651	49826	49826

4.4 ROW Also Exporting More to Other Countries

We look for evidence that "regional" exports to other countries also rise along with their exports to the U.S. In this section, we use UN Comtrade data¹² to study bystander countries' exporting performance. We focus on the U.S.' major trading partners who gained a lot during the trade dispute according to Table 4 and for which monthly import data is available in the UN Comtrade Database.¹³ As a result, we end up with countries/regions of the European Union, ASEAN, Canada, Japan, Korea, and Mexico. The UN Comtrade Database reports imports of products at the HS-6 level, which is thus the level of analysis we use in this section. We aggregate the monthly data to the quarterly level to ease the computation burden.

As such, we estimate the following equation for each country/region c , where c = the European Union, ASEAN, Canada, Japan, Korea and Mexico:

$$\begin{aligned} \log(Exports)_{jct} = & \beta_1 \times Targeted_j \times d_{tar} + \beta_2 \times Targeted_j \times d_{tar} \times \Delta \log(ExpToUS)_{jc} \\ & + \beta_3 \times NonTargeted_j \times D_{tar} + \beta_4 \times NonTargeted_j \times D_{tar} \times \Delta \log(ExpToUS)_{jc} \\ & + \gamma_1 Targeted_j \times t + \gamma_2 NonTargeted_j \times t + \mu_{jc} + \varepsilon_{jt} \end{aligned} \quad (8)$$

$\log(Exports)_{jct}$ is the log of the exports of product j at time t to countries other than the U.S. and China. $\Delta \log(ExpToUS)_{jc}$ is the change in the exports to the U.S. of product j from country/region c , which is a proxy for the impact of the tariff. Targeted products at the HS 6-digit level are those for which a tariff on China was imposed at some point for a product at HS 8-digit level, while d_{tar} as before is a dummy for the period during which the tariff was imposed on product j . Similarly, $NonTargeted_j$ is a dummy for products at the HS 6-digit level if none of HS 8 digit product within the category were tariffed, while D_{tar} takes the value of 1 for any time from Quarter 4 of 2018 and after and 0 for other time periods. Positive estimates of β_2 and β_4 indicate that third countries' exports to countries other than the U.S. and China rose in tandem with the impact of the U.S.-China trade war. We control for linear time trends of targeted and non-targeted products by $Targeted_j \times t$ and $\gamma_2 NonTargeted_j \times t$ respectively.

Evidence in Column (1) in Table 9 suggests that exports of targeted and even non-targeted products by different regions/countries to countries than the U.S. and China did rise. Instead of countries diverting trade in a product to the U.S. from other countries, it looks more like greater exports to the U.S. encouraged greater exports everywhere! Columns (2) - (7) in Table 9 explore the export performance of different regions/countries during the trade dispute. The empirical results suggest that Europe, Korea and Mexico export more

¹²The UN Comtrade Database can be accessed from <https://comtradeplus.un.org>.

¹³Recall that the US census trade data used in the previous sections are at HS 8-digit level.

targeted products to the ROW (other than the U.S. and China), and Korea and Mexico even export more non-targeted products to the ROW.

Table 9: Exports to Countries other than the US and China

	(1) All Areas	(2) ASEAN	(3) Canada	(4) Europe	(5) Japan	(6) Korea	(7) Mexico
$\beta_1 Targeted_j \times d_{tar}$	-0.10*** (0.005)	-0.12*** (0.01)	-0.15*** (0.02)	-0.21*** (0.006)	-0.046*** (0.009)	-0.040*** (0.01)	0.30*** (0.02)
$\beta_2 Targeted_j \times d_{tar} \times \Delta \log(ExpToUS)_j$	0.086*** (0.02)	0.027 (0.05)	0.074 (0.07)	0.076** (0.03)	0.051 (0.04)	0.15*** (0.04)	0.24** (0.1)
$\beta_3 NonTargeted_j \times D_{tar}$	-0.097*** (0.02)	-0.094 (0.08)	-0.20*** (0.08)	-0.21*** (0.03)	-0.085*** (0.03)	0.084 (0.07)	0.54*** (0.1)
$\beta_4 \mathbb{1}\{NonTargeted_j \times D_{tar} \times \Delta \log(ExpToUS)_j\}$	0.082*** (0.03)	0.040 (0.06)	0.080 (0.07)	0.083 (0.07)	0.033 (0.04)	0.16** (0.07)	0.15*** (0.06)
Cons	13.5*** (0.004)	14.2*** (0.01)	11.0*** (0.01)	15.2*** (0.005)	13.5*** (0.008)	13.2*** (0.01)	12.0*** (0.02)
Linear Time Trend by Country	YES	YES	YES	YES	YES	YES	YES
HS6 FE	YES	YES	YES	YES	YES	YES	YES
R-sq	0.910	0.881	0.773	0.932	0.933	0.885	0.819
N	913722	157043	144312	240450	173112	146116	52689

5 Conclusion

In this paper, we have used UN Comtrade data, U.S. import data, the NBER Manufacturing Industry database and the World Bank’s World Integrated Trade Solution database to explore the spillover effects of the U.S.-China trade war in various dimensions and their potential underlying mechanisms. While our findings indicate substantial spillovers of the U.S.-China trade war on U.S. imports of targeted products from bystander countries as well as on non-targeted products, which is consistent with the literature so far, we have also uncovered various significant underlying mechanisms of such effects, which, to our knowledge, no other study has done. Our empirical results present conclusive evidence that a bystander country’s revealed comparative advantage as well as its capital abundance and capital intensity lead to increases in the benefits that it receives from the tariff surges between the U.S. and China. In addition, non-targeted products that are similar to targeted products (identified as products within the same groups of HS classifications) are also affected by the tariffs in terms of the level of U.S. imports from other countries vs. from China via the colocation channel. Finally, when China is hit with a tariff, bystander countries do not seem to re-route their output of the tariffed products to the U.S. from other destinations. Rather, they seem to export more everywhere. This makes sense if firms in bystander countries who enter in response to the tariffs export to the US as well as everywhere else. These results pave the way for further research on how firms reorganize their production at the micro level which can be accomplished via the use of customs data.

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