

How did Chinese exporters manage the trade war?[†]

Liugang Sheng Huasheng Song Xueqian Zheng

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Abstract

This paper studies how Chinese exporters managed the recent US tariff hikes. Contrary to the conventional wisdom of horizontal trade diversion, China did not divert more of its products to other Northern countries but more to the South. Moving down the quality ladder of destinations helps Chinese exporters escape competition for high-quality products in the North and lowers penetration costs in the South. This vertical trade diversion reduces quality-adjusted export prices but raises qualities and gross prices of Chinese diverted exports, particularly in poor countries and for products with high quality scope, implying that it may benefit the South more.

Keywords: Trade war, trade protectionism, trade diversion, quality ladders

JEL codes: F1, F51, O24

[†]Contact information: Sheng, Department of Economics and HKIAPS, The Chinese University of Hong Kong, Hong Kong, lsheng@cuhk.edu.hk; Song, CRPE and School of Economics, Zhejiang University, China, songzju@zju.edu.cn; Zheng, School of Economics, Zhejiang University, China, zhengxq@zju.edu.cn. We thank seminar and conference participants for helpful comments.

I. Introduction

After decades of worldwide trade liberalization, protectionism struck back in 2018 when President Trump launched a trade war with China. The average US tariffs on Chinese exports increased from 3.1% in early 2018 to 19.3% at the end of 2019 (Bown, 2021), triggering China’s retaliatory tariff hikes on US exports. The escalated tariffs covered around two-thirds of bilateral trade between the two superpowers. Since then a burgeoning literature has studied the impacts of the Sino-US trade war on bilateral trade, aggregate welfare, tariff pass-through, output, and consumption (e.g. Fajgelbaum et al., 2020).¹ However, less attention has been paid to how firms reallocate their exports across markets upon tariff shocks. Did China successfully reallocate its exports to other markets? Were Chinese products diverted more to the North or to the South? And did the trade diversion make China’s terms of trade in third markets worse off?

To study how Chinese exporters manage the headwinds of the US tariff shocks through trade diversion, we use the monthly Chinese export data at HS6 product-destination level during 2017-2019. We first present the empirical fact that the US tariffs have a significantly destructive effect on Chinese exports to the US, but not on China’s total exports, suggesting that Chinese exporters have successfully diverted their exports to other countries. By contrast, Benguria and Saffie (2019) find that the increases in US exports to the rest of the world only partially offset the declines in its sales to China. Thus, how did Chinese exporters successfully manage their trade diversion, given that the size of the targeted Chinese exports is more than three times the US exports levied by China?

We distinguish two diversion strategies for Chinese exporters, namely the “*Horizontal Trade Diversion (HTD)*”, referring to the case that Chinese exporters divert their products

¹Fajgelbaum and Khandelwal (2021) deliver a comprehensive review of related studies on these topics. Several other papers have studied a wider array of topics, ranging from global production networks and supply chains (i.e., Huang et al., 2019; Handley et al., 2020; Wu et al., 2021), cooperate investments and market values (i.e., Amiti et al., 2020; Benguria et al., 2022; Wang et al., 2021; Egger and Zhu, 2021), employment and wages (i.e., Flaaen and Pierce, 2020; Chor and Li, 2021; He et al., 2021), to political economy (i.e., Liu and Woo, 2018; Blanchard et al., 2019; Fetzer and Schwarz, 2021; Fan et al., 2022) .

to other countries similar to the US market (the North), and the “*Vertical Trade Diversion (VTD)*” along the quality ladders of destinations, indicating the diversion of the high-quality products from the US to other countries that have incomes lower than the US and initially import lower-quality products from China (the South).

Conventional wisdom suggests that China may follow the HTD strategy by diverting their products more to Northern countries similar to the US market in terms of income level, market access, or consumer preference. However, we find opposite results using four different country-level similarity indices of income level and trade structure between the third markets and the US.² Instead, we find that China has diverted more of the targeted products to the South. Moreover, we also detect a puzzling increase in export prices of Chinese targeted products sold to other countries, which is difficult to be reconciled with the HTD strategy as it implies that more trade diversion should depress Chinese export prices for similar products sold in similar third markets.

By contrast, our study suggests that Chinese exporters adopt the VTD strategy. The recent trade literature on product quality shows that firms usually export more high-quality products to high-income countries with high prices, using both product level or firm-product level data (Bastos and Silva, 2010; Bastos et al., 2018).³ As the US is the largest single market with high incomes, Chinese exports to the US are likely to be high-quality products compared with other destinations (Manova and Zhang, 2012; Fan et al., 2020). Thus, the hike in US tariffs is an external demand shock to the high-quality products that China exports. Chinese exporters would face severe competition for high-quality products in the North if they divert similar-quality products there. To escape from the competition for products with similar qualities in the North, Chinese exporters may redirect their high-quality products to the South which initially imports low-quality products

²These results are also robust to a wide range of controls including common gravity variables such as distance to China, destination income and market size, and destination import growth from other countries.

³Previous literature also shows that quality plays an important role in the direction of trade, vertical specialization, and the price distribution of exports and imports (Schott, 2004; Hummels and Klenow, 2005; Hallak, 2006; Khandelwal, 2010; Feenstra and Romalis, 2014).

from China. Meanwhile, the quality advantage of Chinese exports previously sold in the US makes it easier to penetrate the Southern markets (perhaps with price discounts). Moreover, this vertical trade diversion could lead to a significant quality upgrading in Chinese exports to the South, which in turn increases Chinese export prices and thus improves the gross terms of trade of Chinese goods in those markets.

To explore the patterns of the VTD, we estimate the time-varying product quality and quality-adjusted export price at product-destination level, following the method of [Khandelwal et al. \(2013\)](#). We find that the US tariffs lead to a significant quality upgrading in the targeted Chinese products diverted to third markets. After controlling for the quality upgrading, the US tariffs indeed reduce the quality-adjusted price of the Chinese products exported to third markets due to the excessive supply from trade diversion. This suggests that China's quality-adjusted terms of trade in third markets are likely to be worse off if China's quality-adjusted import prices do not change substantially. However, the quality upgrading effect dominates the supply effect of trade diversion, leading to a net increase in the Chinese Free on Board (FOB) export prices of the targeted products sold in third markets. Moreover, we also find that the quality upgrading of Chinese exports is more significant in poor countries, consistent with the fact that the quality gap between Chinese exports to the US and to the South is likely to be larger. This evidence suggests that upon the US tariff shocks, Chinese exporters are moving down along the quality (and income) ladders of destination countries.

In addition, we also find that US tariffs increase the extensive margin of Chinese exports to third markets, particularly in the South. This indicates that the penetration cost might be lower in those countries thanks to the quality advantage of Chinese products previously sold in the US, and thus Chinese exporters introduce more product varieties to those destinations.

We further utilize the rich heterogeneity in products and firms to support the VTD strategy. We start with the cross-product heterogeneity in quality scope. Recent studies

have shown that products have various scopes of product quality variations (Khandelwal, 2010; Fan et al., 2015; Flach and Unger, 2022). For example, differentiated products usually have larger variations in quality than homogeneous products. We expect that vertical trade diversion and quality upgrading of Chinese exports in third markets should be more prevalent in products with high quality scope. Thus, we construct three different indicator variables of high quality scope for each HS6 product, and the regressions consistently show that quality upgrading and trade diversion of Chinese exports in third markets are more significant for products with high quality scope.

The second heterogeneity is the exporter ownership. Chinese export data at the firm-product level in 2016 shows that foreign-invested enterprises (FIEs) concentrate more on high quality scope products based on the R&D intensity than State-owned enterprises (SOEs) and other private-owned enterprises (POEs). 59% of FIE exports are high quality scope products while this statistic is only 48% and 40% for POEs and SOEs, respectively. As a result, we find that the trade diversion and quality upgrading pattern are more significant for FIEs than POEs, while SOEs are less market-driven and may bear additional policy considerations (Benguria and Saffie, 2021; Chen et al., 2022).

We further exclude two other alternative forces for trade diversion. First, one may argue that China's turning toward the South is driven by the rising political risk or trade policy uncertainty in the US allies which are usually advanced economies. We construct bilateral political distance to the US (or to China) as the gap between their ideal points which represent the country's political orientation, by using the votes in the United Nations General Assembly (UNGA) (Bailey et al., 2017). Moreover, we also construct the changes in the trade policy uncertainty index (ΔTPU) from Ahir et al. (2022). Our baseline results are robust after controlling for political relationships and trade policy uncertainty, although China indeed diverted less to the US allies and more to its foreign friends. Second, to meditate the concerns of tariff evasion through entrepôt trade (Fisman and Wei, 2004; Ferrantino et al., 2012), we exclude 20 countries that have free trade

agreements with the US as Chinese exporters may choose them to enjoy preferential tariff rates in addition to the US tariffs evasion when re-exporting to the US. Moreover, we also exclude 9 suspicious entrepôt countries that see both significant increases in Chinese exports and US imports of the targeted products. Our results are robust to those alternative samples, suggesting that tariff evasion is not the driving force for the pattern of VTD.

Lastly, we check the dynamic responses of trade diversion and quality upgrading to the US tariff shocks by adopting a dynamic DID approach similar to [Fajgelbaum et al. \(2020\)](#). We find that the effects are persistent and slowly increasing over time, indicating that it may take time for marketing and establishing new trade networks in third markets.

We conduct two sets of robustness checks on export prices and VTD respectively. Note that one key evidence supporting the VTD is the positive effect of the US tariffs on the export prices of Chinese products diverted to third markets. However, the export price measured as the unit value may reflect quality, as well as markup and unit costs. Thus, in the first set of robustness checks, we show that neither markup adjustment nor unit cost changes can account for the positive effects of the US tariffs on Chinese export prices in third markets.

Next, we focus on the robustness checks for the VTD. First, our results are insensitive to the choice of the substitution elasticity in estimating the product quality by either choosing a fixed value such as $\sigma = 5$ or a more dis-aggregated one varying across destination-HS4 sector level ([Soderbery, 2018](#)). Second, we use the full sample of Chinese trade partners and the results are similar, suggesting that our conclusions are not sensitive to the inclusion of small trade partners.

Our paper belongs to the expanding literature evaluating the economic effects of the US-China trade war. Recent studies mainly focus on the aggregate welfare consequences of trade barriers and the global reallocation of trade and production. From an ex-ante perspective, a few studies in early 2018 simulate the possible welfare effects of the US-China trade war under different hypothetical scenarios, by using the multi-country multi-

industry trade model based on [Caliendo and Parro \(2015\)](#) ([Guo et al., 2018](#); [Li et al., 2018](#); [Bouët and Laborde, 2018](#)). More post-event empirical assessments arise as the incident unfolded. [Amiti et al. \(2019\)](#) and [Fajgelbaum et al. \(2020\)](#) both find a complete pass-through of US tariffs to its domestic buyers and a relatively small welfare loss relative to GDP for the US economy. [Ma et al. \(2021\)](#) and [Chang et al. \(2020\)](#) implement their specifications from the perspective of China and find similar results. [Ju et al. \(2020\)](#) develop a quantitative trade model with external economies of scale to estimate the welfare costs of the trade war and discuss the optimal industrial policy. Also focusing on China's welfare implication, [Chen et al. \(2022\)](#) further take the non-tariff barriers into consideration. We contribute to this literature by highlighting the role of product quality in trade diversion and providing extensive evidence supporting that China successfully diverted its exports along the quality ladders of destinations. This observation is particularly important for welfare analysis using quantitative trade models, as ignoring the quality upgrading of Chinese products in third markets may underestimate the gains of those countries and also lead to a biased estimate of China's welfare loss.

Our paper is also closely related to the empirical studies focusing on the effects of the tariff war on trade patterns among the US, China, and other countries, such as [Benguria and Saffie \(2019\)](#), [Benguria and Saffie \(2021\)](#), [Jiao et al. \(2021\)](#), [Fajgelbaum et al. \(2021\)](#), [Ma and Meng \(2021\)](#), [Jiang et al. \(2022\)](#) and [Shen et al. \(2021\)](#). All of them find that the tariff war has a significantly destructive effect on bilateral trade between the US and China, as well as some degree of trade diversion. However, none of them distinguishes the HTD and VTD strategies. Up to the best of our knowledge, this paper is the first to uncover a "vertical trade diversion" pattern when Chinese exporters divert their products from the US market to third markets, thanks to the unique opportunity provided by the large-scale tariff war between the two largest economies in the world.

Lastly, our work also contributes to the literature on the role of quality in international trade. Product quality is extensively documented as one of the important determinants

of trade patterns (Hummels and Klenow, 2005; Hallak, 2006; Khandelwal, 2010; Hallak and Schott, 2011), meanwhile the impacts of trade and related policies on product quality upgrading have also been intensively studied recently (Verhoogen, 2008; Fan et al., 2015; Flach, 2016; Fieler et al., 2018). Our paper is mostly close to Feenstra (1988) and Goldberg (1995) documenting that Japanese automakers substantially upgraded their exports to the US when they were subject to quota constraints, as our study also highlights the critical role of quality margin adjustment for firms in response to the headwinds in foreign markets.

The remainder of the paper is organized as follows. Section I presents the background of the trade war and data sources. Section II presents the overall effects of the US tariff shocks on Chinese exports. Section III discusses trade diversion, and Section IV presents the robustness analysis. Section V briefly concludes.

II. The US-China trade war and data

II.A. A brief review of the US-China trade war

The US-China trade war unfolded over a series of tariff escalations from both belligerents during 2018-2019. Starting from June 2018, the US has imposed three waves of tariff hikes on \$50 billion, \$200 billion, and \$300 billion of Chinese exports with tariff rates ranging from 10%, 15% to 25%, based on Section 301 investigations. Accordingly, China also retaliated by increasing tariffs on imports from the US. In this study, we focus on the US's Section 301 tariffs as well as Section 232 national security tariffs on Chinese products. According to Bown (2021), 67% of US imports from China were covered by the two lists of special tariffs in January 2021, based on the US imports data in 2017. Moreover, 66.4% of US imports from China are under Section 301 tariffs, while the Section 232 tariffs on steel and aluminum products cover 0.6% of US imports from China, and most of them are also included in the Section 301 tariffs.

II.B. Data

To understand how China responded to the US tariff shocks, we use the publicly available Chinese monthly product-level trade data from January 2017 to December 2019. The monthly Chinese trade data contains information on the export (import) value, quantity, customs regimes, province-level locations of domestic exporters (importers), and destination (origin) markets for each product at HS8 digit level. Our full sample of Chinese exports covers 241 partners, 8045 HS8 digit products, and 39,769,272 observations. For the analysis of trade diversion, we drop the countries to which China exported less than 500 million USD in 2017 to avoid possible bias from small trade values and low trading frequencies and to obtain more accurate estimates of quality and quality-adjusted prices. The remaining sample covers 131 non-US countries and accounts for more than 99.4 percent of Chinese (non-US) total exports.⁴ We also confirm that our main results are robust if we include small trading partners in regressions in the robustness section.

Note we use the publicly available monthly Chinese exports data at the product level during 2017-2019 for our empirical analysis, as we do not have access to the confidential monthly firm-product level customs data for those years. Although it is intriguing to examine how individual firms adjust their quality upon the US tariff shocks, it may be more suitable to use product-level data to detect the quality adjustment along trade diversion for two reasons. First, the quality upgrading analysis at the product-destination level captures both within-firm and between-firms changes in quality for the same product-destination pair. Second, many firms may export a few varieties with different qualities for the same product to multiple countries, thus it may be difficult to detect the quality upgrading within the firm-product-destination cell.

The original US tariffs downloaded from the Federal Register website are at HS8 level, but the HS codes between the US and China are only consistent at 6 digits. Thus, we compute the average US tariffs at HS6 weighted by the US imports from China at HS8 digit

⁴See Appendix Table A.1 for the list of Chinese 131 trading partners.

in 2017. The US’s Section 301 tariffs and Section 232 national security tariffs on Chinese products have increased the weighted average tariff rates by 15.7 percentage points by December 2019, using the weights of China’s exports to the US in 2017. Accordingly, the price of Chinese FOB export products is measured as the unit value at HS6 product level and our regressions on Chinese exports are at HS6 product level.

III. The impact of US tariffs on Chinese exports

We first study the destructive effect of the US tariffs on Chinese exports to the US by using the following econometric specification:

$$\ln Y_{kt}^d = \beta_0 + \beta_1 \ln(1 + \tau_{kt}^{US}) + \alpha_{km} + \alpha_t + \varepsilon_{kt} \quad (1)$$

where Y_{kt}^d are variables of interest such as the export value, quantity, FOB export unit price of Chinese product k shipped to the destination $d = US$ at monthly time t . τ_{kt}^{US} is the US tariffs on the product k importing from China at time t . α_{km} is HS6 product-month fixed effects which capture the product-specific seasonal effects, and α_t is the year-month time fixed effects capturing macroeconomic conditions of the importing and exporting countries.

The first two columns in Table 1 show that the US tariffs significantly reduces Chinese exports to the US both in values and quantities, and the estimated elasticities are slightly above 1, close to the estimates in [Fajgelbaum et al. \(2021\)](#). More specifically, on average one percentage point increase in the US tariffs reduce Chinese exports to the US by about 1.09 percent in values and 1.08 percent in quantities, respectively. Moreover, the US tariffs do not have significant effects on the FOB export prices of Chinese products shipped to the US, as the estimate of US tariff in column (3) is close to zero. These results are largely consistent with the previous findings in [Fajgelbaum et al. \(2020\)](#) and [Cavallo et al. \(2021\)](#),

Table 1: Chinese exports to different markets

<i>Trade Partner</i>	US			R.o.W.	World
	<i>Ln(exp)</i> (1)	<i>Ln(quan)</i> (2)	<i>Ln(price)</i> (3)	<i>Ln(exp)</i> (4)	<i>Ln(exp)</i> (5)
<i>Ln(1+UStar)</i>	-1.089*** (0.10)	-1.078*** (0.11)	-0.011 (0.06)	0.155** (0.07)	0.011 (0.07)
<i>Constant</i>	13.367*** (0.01)	11.191*** (0.01)	2.177*** (0.00)	15.076*** (0.00)	15.214*** (0.00)
<i>HS6-Month FE</i>	+	+	+	+	+
<i>Time FE</i>	+	+	+	+	+
<i>Adj. R²</i>	0.885	0.913	0.925	0.927	0.931
<i>N</i>	126245	126245	126245	166838	167504

Note: Robust standard errors clustered at the product level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

as well as [Jiao et al. \(2021\)](#) who use the firm-level data from a prefecture city in China. ⁵

The impact of the US tariff hikes on Chinese exports to the US is largely expected, but how did Chinese firms manage and respond to the tariff war? To capture the possible overall trade diversion effects, we also use the log values of Chinese exports to the rest of the world ($d = R.o.W.$) and Chinese total exports ($d = World$) as the dependent variables in the above regression, and report the results in column (4) and (5) of Table 1. Overall, we find a significant trade diversion as Chinese firms export to other countries more for the products facing higher US tariffs, and the trade diversion largely offsets the negative effects of US tariffs on China’s exports to the US. As a result, the US tariffs have a negligible effect on China’s total exports during 2018 and 2019, as shown in column (5). In terms of magnitude, we calculate the monthly Chinese export loss in the US market and export diversion to the rest of the world based on the regression results in columns (1) and (4). As shown in Figure B.2, these two numbers are very close. In total, the cumulative export loss of China’s exports to the US is 57.6 billion USD while the increase in China’s exports

⁵In Appendix B.1, we adopt the approach of the event study by using a multi-period Differences-in-Differences (DID) setting to show the dynamic average effects of the US tariffs on Chinese exports and the parallel trends for the levied products and non-levied goods ([Fajgelbaum et al., 2020](#)). The results are similar and Figure B.1 also shows the trend similarity between products in treatment and control groups of Chinese products.

to other trade partners is 50.3 billion USD by the end of 2019, indicating that the diverted exports compensate for about 90% of Chinese export loss in the US market. By contrast, [Benguria and Saffie \(2019\)](#) find that the increase in the US exports to the rest of the world offsets only about half of the loss in its exports to China. As the targeted Chinese exports by the US are more than three times the US exports levied by China, it must be even more challenging for China to divert their exports than the US. Thus, how did Chinese firms successfully manage to divert their exports to other markets?

IV. Trade diversion

In this section, we study Chinese exporters' trade diversion strategy by employing the monthly Chinese product-level export data broken down by destination markets. Note from now on we use the sub-sample of 131 non-US major trade partners by dropping the small trade partners to which China exported less than 500 million USD in 2017 to avoid possible bias from small trade values and low trading frequencies. We first estimate the elasticity of Chinese exports to other countries with respect to the US tariffs by using the following simple econometric specification:

$$\ln Y_{ckt} = \gamma_0 + \gamma_1 \ln(1 + \tau_{kt}^{US}) + \gamma_2 \ln(1 + \tau_{kt}^{US}) \times X_c + \alpha_{km} + \alpha_{ct} + \alpha_{ch} + \epsilon_{ckt} \quad (2)$$

where Y_{ckt} is the variable of interest such as export value and quantity of Chinese product k shipping to the non-US destination country c at monthly time t . We interact the US tariffs with destination c characteristics denoted by X_c to explore where Chinese exporters manage to divert their products. We demean all variables in X_c (except for dummy variables) before interacting them with the US tariffs, and thus γ_1 presents the average effects of the US tariffs for the mean values of X_c . α_{km} is the HS6 product-month fixed effects which capture the product-specific seasonal effects, and α_{ct} is the destination-time fixed effects which capture the time-varying factors of the destination countries. α_{ch} is the

destination-HS2 sector fixed effects capturing the cross-country differences in HS2 sectors. We also cluster the standard error at the country-product level to control for possible correlations within the country-product pair.

We first report the results without including any interaction terms in regression in column (1) in Table 2. As expected, the average elasticity of Chinese exports to other countries w.r.t the US tariffs, γ_1 , is significantly positive, suggesting that Chinese firms divert their exports from the US to other countries.

To further show the cross-country heterogeneity in the elasticity of Chinese exports to other countries w.r.t the US tariffs, we estimate the destination-specific tariff elasticities by interacting the destination indicator with the US tariffs. Figure 1 plots the estimated destination-specific tariff elasticities against destination characteristics such as log real GDP per capita ratio and log real GDP ratio (relative to the level of the US in 2016), as well as the log distance to China. Surprisingly, we find that these trade diversion tariff elasticities are higher in poorer countries, suggesting that Chinese firms may divert their exports from the US to other countries with lower income levels. In addition, panels (b) and (c) in Figure 1 show that China also diverts its exports more to countries closer to China and with a smaller market size.

Based on those observations, we include in regressions the interactions of the US tariffs with the real GDP per capita ratio, real GDP ratio (both relative to the level of the US in 2016), as well as the log distance to China. The results in column (2) of Table 2 show that the estimated coefficients of those three interaction terms are significantly negative, consistent with results in Figure 1.

One may be wondering that China may divert its exports more to countries with higher import growth. Thus, we compute the annual growth of the country c 's imports from other countries except the US and China for each HS4 product category that the product variety k belongs to, and include its interaction with the US tariffs in the regression. Column (3) in Table 2 shows that the estimation results are very similar to column

(2) and the import growth in the destination country has a positive but insignificant effect on Chinese exports' diversion elasticity. Column (4) adopts an alternative triple country-sector (HS2)-time fixed effects to control for unobserved time-varying sectoral factors in the destination market, in addition to the product-month fixed effect, and our results still hold. Moreover, the trade diversion pattern also holds if we use the log export quantity as the dependent variable, as shown in columns (5) to (8).

Based on our baseline results in column (3), we have an estimate of 0.37 for product-level trade diversion elasticity on an average destination market. This implies successful trade diversion as Chinese exports to the 131 non-US major trade partners are about 4.5 times its exports to the US during our sample period, and the trade destruction elasticity is 1.09 in the US market (in column (1) of Table 1). The interaction terms in column (3) suggest that the real GDP per capita ratio, the real GDP ratio and geographic distance (to China) are all playing important roles in determining the trade diversion in a specific destination. In terms of magnitudes, if one country's real GDP per capita ratio is 10 percentage points below the sample average, China's trade diversion elasticity would increase by 0.128 and raise to 0.50 ($=0.372+0.128$). Similarly, if one country's GDP ratio is 10 percentage points below the sample average, China's trade diversion elasticity would increase by 0.609 and raise to 0.981 ($=0.372+0.609$). And if the distance between the third market and China is 10 (log) percentage points closer than the sample average, the diversion elasticity to this destination market would increase by 0.099 and raise to 0.471($=0.372+0.099$). Note that a higher trade diversion elasticity for a particular third market does not necessarily imply that China would divert more of its products to this country in terms of export value, as China's initial export value in that market also matters. Thus, when we say that China diverts more to a third market, we are particularly referring to the high trade diversion elasticities in that market.

Table 2: Trade diversion effect

Dependent Variable	Ln(exp)				Ln(quant)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+UStar)	0.331*** (0.02)	0.357*** (0.02)	0.372*** (0.02)	0.181*** (0.02)	0.202*** (0.02)	0.230*** (0.02)	0.243*** (0.02)	0.115*** (0.02)
Ln(1+UStar) × GDPcapRatio		-1.288*** (0.09)	-1.278*** (0.09)	-1.596*** (0.14)		-0.763*** (0.10)	-0.757*** (0.10)	-0.924*** (0.15)
Ln(1+UStar) × GDPRatio		-6.482*** (0.67)	-6.091*** (0.68)	-9.394*** (0.99)		-4.895*** (0.74)	-4.393*** (0.76)	-7.464*** (1.11)
Ln(1+UStar) × Ln(Dist)		-0.994*** (0.05)	-0.989*** (0.05)	-1.405*** (0.07)		-1.012*** (0.05)	-1.006*** (0.05)	-1.414*** (0.07)
Ln(1+UStar) × ImpGrowth			0.009 (0.03)	-0.017 (0.03)			0.022 (0.03)	-0.002 (0.03)
Constant	10.544*** (0.00)	10.554*** (0.00)	10.547*** (0.00)	10.564*** (0.00)	8.431*** (0.00)	8.434*** (0.00)	8.422*** (0.00)	8.432*** (0.00)
HS6-Month FE	+	+	+	+	+	+	+	+
Country-HS2 FE	+	+	+		+	+	+	
Country-Time FE	+	+	+		+	+	+	
Country-HS2-Time FE				+				+
Adj. R ²	0.528	0.531	0.532	0.531	0.683	0.685	0.683	0.681
N	7736545	7466650	7156397	7111329	7736545	7466650	7156397	7111329

Note: The sample includes all monthly export records with 131 non-US major trade partners to whom China's exports exceed \$500 million. The dependent variables are the logarithm of Chinese exports (both value and quantity) to the third market c . The first three interactions of US tariffs with real GDP per capita ratio (to US), real GDP ratio (to US), and (logarithm of) distance between the destination's capital and Beijing (China), respectively, are included to control for destination-level heterogeneity in column (2) and (6). The fourth interaction with time-varying destination-HS4 digit import growth is used to account for demand-side sectoral shocks in the destination market. Note, we demean these four variables before we take the interaction terms and right-winsorized ImpGrowth at the 99th percentile. Robust standard errors clustered at the country-product level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

IV.A. Horizontal trade diversion

The conventional wisdom suggests that Chinese exporters may divert their products more to third markets similar to the US, as their income level, market access cost, and consumer preference over Chinese products may be similar.⁶ For example, Lenovo may export more of its flagship laptop Thinkpad to the European market than other developing countries such as India after the US imposes high tariffs on its exports, as the income level, consumer preference, and market structure in Europe are similar to the US market. However, one disadvantage of this strategy is that the trade diversion may intensify the competition within the high-quality goods, and Chinese exporters have to pay high marketing costs or reduce their export prices to attract more consumers in those countries similar to the US.

Our previous results seem to be at odds with this strategy, but to formally test whether Chinese firms adopt the HTD strategy, we construct four measures of market similarity between the US and the third market c . Following [Finger and Kreinin \(1979\)](#) and [Schott \(2008\)](#), we first construct the import similarity index w.r.t the US, by using the import data of each country in 2016, $ImpSI_c = \sum_K \min\left\{\frac{Imp_{c,K}^{world}}{\sum_K Imp_{c,K}^{world}}, \frac{Imp_{us,K}^{world}}{\sum_K Imp_{us,K}^{world}}\right\}$, where $Imp_{c,K}^{world}$ indicates country c 's import value of product group K (defined at HS4 digit level) from all partners. Similarly, we construct the export similarity index which measures the similarity of the product mix between China's exports to the destination c and to the US, $ExpSI_c = \sum_K \min\left\{\frac{Exp_{c,K}^{chn}}{\sum_K Exp_{c,K}^{chn}}, \frac{Exp_{us,K}^{chn}}{\sum_K Exp_{us,K}^{chn}}\right\}$, Similar to $Imp_{c,K}^{world}$, $Exp_{c,K}^{chn}$ stands for exports of product group K from country c to China. To compute the first two similarity indexes, we collect the bilateral trade flows in 2016 from the BACI database of CEPII, which is built from data directly reported by each country to the United Nations Statistical Division (UN Comtrade).

The third is the income (level) similarity between the third country and the US,

⁶Recently, a large literature has documented that firms tend to export to countries similar to their prior destinations in terms of geographic location, language, and income per capita, e.g., [Eaton et al. \(2008\)](#); [Lawless \(2009\)](#); [Chaney \(2014\)](#); [Defever et al. \(2015\)](#); [Morales et al. \(2019\)](#); [Arkolakis et al. \(2021\)](#).

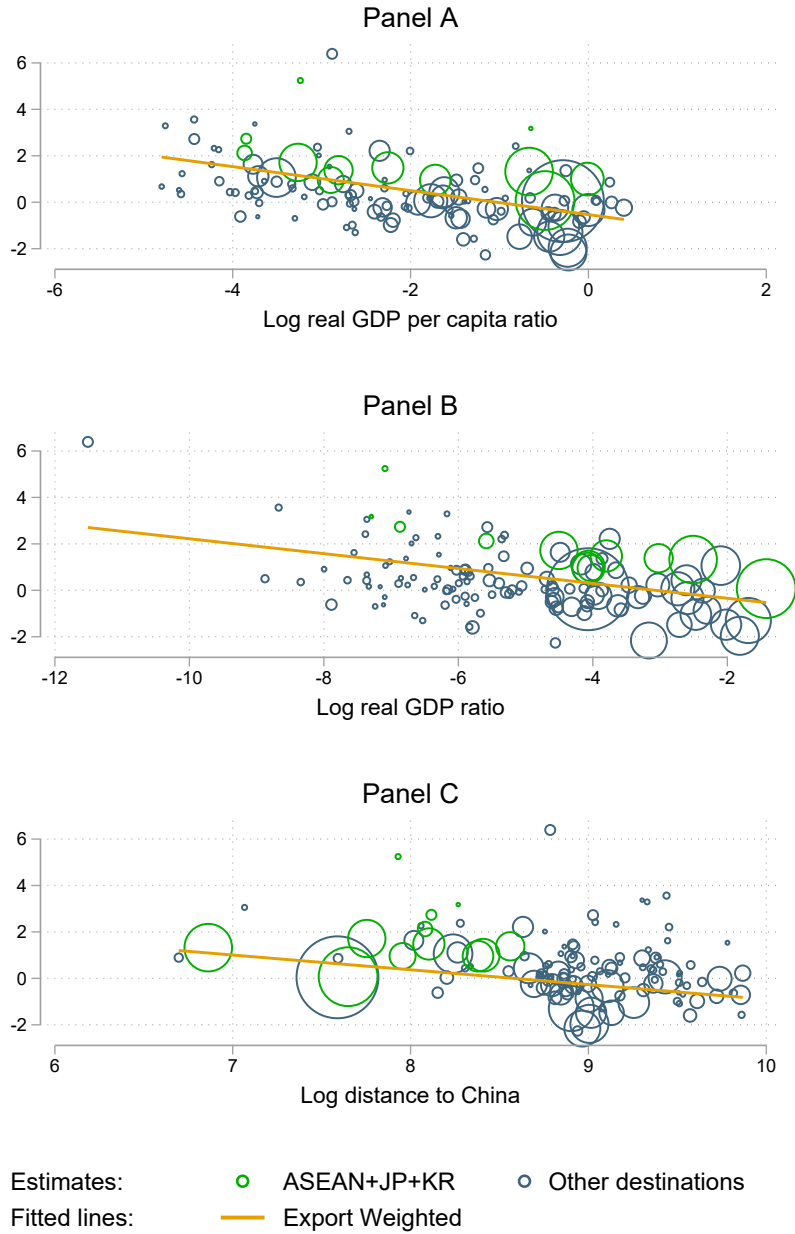


Figure 1: The destination-specific trade diversion elasticity

Note: This figure plots the estimated destination-specific trade diversion elasticities over different destination's characteristics. The elasticities are obtained from a regression of log export values on the tariff variable interacted with destination dummies, where product-month, destination-sector, and destination-time fixed effects are included, i.e., $\ln Y_{ckt} = \gamma_0 + \sum_i \gamma_i \ln(1 + \tau_{kt}^{US}) \times \mathbb{I}\{i = c\} + \alpha_{km} + \alpha_{ct} + \alpha_{ch} + \varepsilon_{ckt}$. Fitted lines are weighted by bilateral exports to each destination in 2016, and weights are indicated by the sizes of circles.

$IncSI_c^l = -|\ln(y_c) - \ln(y_{us})|$, where y_c and y_{us} are the real GDP per capita of country c and the US in 2016, respectively. As the average income similarity may not fully capture the income distribution overlap between two countries, we also use the income distribution similarity index following the practice of [Bernasconi \(2013\)](#). With $f_a(x)$ denoting the probability density function (pdf) at income level x of country $a \in \{c, us\}$, the income distribution overlap between country c and the US is defined as $IncSI_c^o = \int_x \min\{f_c(x), f_{us}(x)\}dx$. Empirically, we use income shares of deciles from the World Inequality Database to compute a discrete empirical income distribution for each country in 2016 and add the overlap ratio in every discrete income interval to get the country-pair income distribution overlap. More details can be found in [Appendix A.3](#). Intuitively, our four country similarity indices capture the similarity of the import demands between the third market and the US, from the perspectives of the import mix, China's export mix, average income level, and income distribution.

Because those four similarity measures are highly correlated, we include the interaction terms of each of them with the US tariffs one by one in each regression. If the conventional wisdom is correct, high US tariffs make China export more products to countries similar to the US market, we expect that the estimated coefficients of those interaction terms should be positive. However, surprisingly we find the opposite results. As shown in [Table 3](#), all the coefficients of the interaction terms of the four similarity measures and the US tariffs are significantly negative, suggesting that Chinese firms in fact export more to markets that are different from the US market for the products facing high tariffs in the US. The results also hold if we use export quantity rather than export value as the dependent variable. Moreover, this finding is robust to additional interaction control variables such as distance to China, market size, and import growth potentials, as well as to alternative sets of fixed effects such as product, destination, and time fixed effects or HS6 product-month and destination-HS2-time fixed effects, which may better capture the time-varying sectoral market conditions in destination countries.

IV.B. Vertical trade diversion

The recent trade literature has documented that quality plays an important role in the direction of trade, vertical specialization, and the price distribution of exports and import prices (Schott, 2004; Hummels and Klenow, 2005; Hallak, 2006; Khandelwal, 2010; Feenstra and Romalis, 2014; Fajgelbaum et al., 2011; Ludema and Yu, 2016). Using detailed product-level data, Schott (2004) show that export unit values increase systematically with exporter per capita income and relative endowments of physical and human capital, and Hallak (2006) also show that rich countries tend to import relatively more from countries that produce high-quality goods. Using firm-product-destination trade data, Bastos and Silva (2010) and Manova and Zhang (2012) show that Portuguese and Chinese firms export high-quality goods to high-income countries.

As the US is the largest single market with high income per capita, Chinese exports to the US are likely to be high-quality products, and thus Chinese exporters may divert their products along the quality ladders, i.e., divert high-quality products away from the US to other countries that initially import low-quality products from China. In the previous section, we found evidence that Chinese firms divert their exports more to countries with lower income levels compared with the US, which is consistent with the fact that low-income countries usually import low-quality products. Moreover, those countries may have higher import potential for the high-quality products that the Chinese firms initially export to the US.

Table 3: Horizontal trade diversion

Dependent Variable	Ln(exp)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(1+UStar)	0.333*** (0.02)	0.382*** (0.02)	0.333*** (0.02)	0.387*** (0.02)	0.337*** (0.02)	0.368*** (0.02)	0.337*** (0.02)	0.367*** (0.02)
Ln(1+UStar) × ImpSI	-6.304*** (0.24)	-5.087*** (0.30)						
Ln(1+UStar) × ExpSI			-5.866*** (0.20)	-5.405*** (0.25)				
Ln(1+UStar) × IncSI ^l					-0.481*** (0.02)	-0.447*** (0.02)		
Ln(1+UStar) × IncSI ^o							-3.168*** (0.15)	-2.928*** (0.16)
Constant	10.540*** (0.00)	10.543*** (0.00)	10.540*** (0.00)	10.543*** (0.00)	10.544*** (0.00)	10.547*** (0.00)	10.561*** (0.00)	10.545*** (0.00)
Control variables		+		+		+		+
Fixed effects		+	+	+	+	+	+	+
Adj. R ²	0.529	0.532	0.529	0.532	0.531	0.532	0.531	0.532
N	7586285	7191813	7586285	7191813	7505652	7156397	7621260	7184774

Note: The sample is the same as in Table 2. The dependent variable is the logarithm of Chinese exports to the third market c . The control variables include three interactions of US tariffs with the relative GDP ratio, the distance between the destination capital and China, and the import growth in the destination market. Note, we demean these four variables before we take the interaction terms. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled, and robust standard errors clustered at the country-product level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Note when we take into account the quality of exports, the trade diversion may have two opposite effects on the FOB price of the Chinese products exported to other markets. First, given the demand in third markets, an exogenous increase in the supply of the product by Chinese exports tends to depress Chinese exporting prices in third markets. However, the Chinese products diverted from the US may have higher qualities compared with products that Chinese firms have already exported to third markets. For example, Lenovo may initially export high-end computers to the US while exporting low-end computers to developing countries such as Vietnam and India. Upon the US tariff shock, Lenovo may export more high-end computers to Vietnam and India. This quality upgrading effect associated with trade diversion may increase the FOB price of Chinese products sold to third markets. As the supply effects and quality effects are offsetting each other, the effects of trade diversion on Chinese FOB price in third markets are ambiguous.

(1) Baseline results of quality upgrading

To test the quality upgrading along trade diversion, we follow [Khandelwal et al. \(2013\)](#) to estimate the quality and the quality-adjusted price, and study how the US tariffs affect Chinese export prices in third markets through two channels. More specifically, we estimate the effective quality of exported product k from China shipping to destination country c in time t . Assume that consumers' preference is $U = (\int_{k \in \Omega} (\lambda_c(k) q_c(k))^{(\sigma-1)/\sigma} dk)^{\sigma/(\sigma-1)}$ where q denotes quantity of consumption and λ indicates quality. The demand is given by $q_c(k) = \lambda_c^{\sigma-1}(k) p_c^{-\sigma}(k) P_c^{\sigma-1} Y_c$ where Y_c is the total income in country c . Taking logs, the quality for each product-country-time observation can be estimated as the residual from the following OLS regression with the assumption of a particular value for σ ,

$$\ln(q_{kct}) + \sigma \ln(p_{kct}) = \alpha_k + \alpha_{ct} + \epsilon_{kct} \quad (3)$$

where country-time fixed effect α_{ct} collects the destination country's income and price index, and the product fixed effect α_k captures the difference in prices and quantities across product categories due to the inherent characteristics of products. Thus, the estimated (log) quality is $\ln(\hat{\lambda}_{kct}) = \hat{\epsilon}_{kct}/(\sigma - 1)$, and the (log) quality-adjusted prices are $\ln(p_{kct}) - \ln(\hat{\lambda}_{kct})$. The intuition behind this approach is that conditional on price, a variety with a higher quantity is assigned higher quality.

For the value of σ , the simplest approach is to use the same value, such as $\sigma = 5$, or 10 for all products. However, this approach ignores the large heterogeneity in the substitution elasticity across products as shown in [Broda and Weinstein \(2006\)](#).⁷ Thus, similar to [Fan et al. \(2015\)](#), we adopt the estimated σ at SITC 3 digit level provided by [Broda and Weinstein \(2006\)](#) for the estimation of product quality and quality-adjusted price.

We first estimate the product quality for Chinese exports to 131 non-US countries and the US in 2017, the year before the outbreak of the trade war. Our estimated quality shows a consistent pattern with the existing literature that Chinese exports to richer countries (i.e., the US) tend to have higher quality ([Manova and Zhang, 2012](#); [Manova and Yu, 2017](#)). As two examples are shown in [Figure 2](#), where toys as an example of labor-intensive products and laptops an example of capital-intensive/technology-intensive products, the price, and quality of products exported to the US are higher than most low-income destinations.⁸

Next, we use Chinese exports to all 131 non-US countries in the full sample period to estimate the quality and quality-adjusted price of the Chinese HS6 products sold in different markets. After that, we use the same econometric specification (2) for regressions to study the effects of the US tariffs on the export unit value, quality, and quality-

⁷The elasticities of SITC 3-digit products estimated by [Broda and Weinstein \(2006\)](#) span from 1 to over 100, and the standard deviation is 8, about two times its average of 4. The large variation in the estimated demand elasticities across products suggests that we use the SITC 3-digit product level σ , instead of choosing a uniform value for all products.

⁸We also plot the distributions of the estimated quality of Chinese exports to the US and to other countries in [Appendix Figure A.1](#). It clearly shows that before the trade war, the quality distribution of Chinese exports to the US is skewed toward the right compared with the distribution of Chinese exports to other countries.

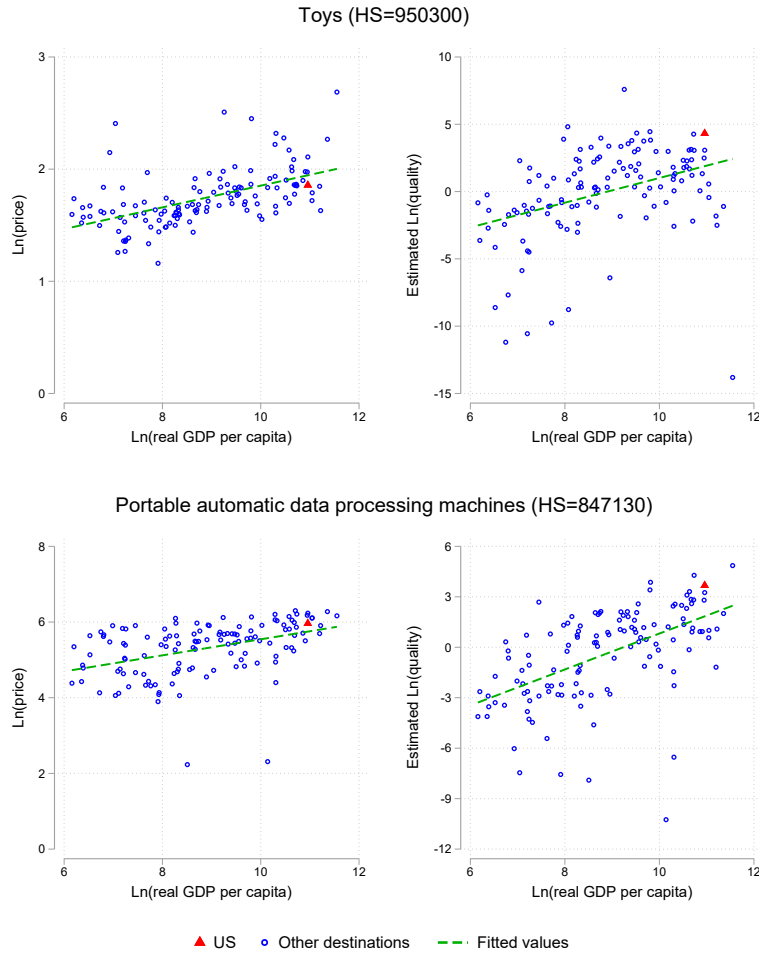


Figure 2: Two examples of products exported to the US and other destinations

adjusted price of the Chinese exports to other countries, controlling for HS6 product-month, country-HS2, and country-time fixed effects. Note the quality-adjusted price purges the quality differences in products and thus reflects the supply effects of trade diversion due to the US tariffs. Thus, the decomposition of the unit value of Chinese exports allows us to disentangle the supply effects and quality upgrading effects of the trade diversion on Chinese FOB export price.

The first three columns in Table 4 present the effects of the US tariffs on the unit value, quality-adjusted price, and quality of the Chinese exports to the third country, without controlling for additional interaction terms with the US tariffs. Two interesting findings emerge. First, contrary to the conventional wisdom that trade diversion should lead to

a decline in the unit value of Chinese exports to other countries, we find that the US tariffs actually increase the unit value of Chinese exports to the third country, as shown in column (1). Second, this positive effect is completely driven by the quality upgrading associated with trade diversion in third markets, as the results in columns (2) and (3) show that the US tariffs have negative effects on the quality-adjusted price but positive effects on quality upgrading of Chinese exports to third markets. In other words, the trade diversion indeed reduces the quality-adjusted price of the Chinese exports to third markets, however, it also leads to quality upgrading in the Chinese exports in those countries as the qualities of the Chinese goods previously sold to the US are relatively higher than the products sold in those countries. Thus, our results are consistent with the story of VTD.

In terms of magnitude, a 10 percentage point increase in the US tariffs will reduce the quality-adjusted price of Chinese exports sold to third markets by 3.4 percent. This calculation suggests that China's quality-adjusted terms of trade are likely to be worse off due to the trade diversion if the quality-adjusted import prices of China do not change substantially. However, the same change in the US tariffs also increases the quality of Chinese exports to third markets by about 4.8 percent as shown in column (3). This quality upgrading effect dominates the supply effect of trade diversion and thus overall a 10 percent increase in the US tariffs raises Chinese export prices in third markets by 1.3 percent.⁹

⁹The elasticity of Chinese export prices in the third market w.r.t the US tariffs does not exactly equal to the sum of the elasticities of qualities and quality-adjusted prices of Chinese exports in the third market w.r.t the US tariffs, due to the slight differences in the samples as shown in Table 4.

Table 4: Vertical trade diversion

<i>Dependent Variable</i>	Ln(price) (1)	Ln(qap) (2)	Ln(quality) (3)	Ln(emargin) (4)	Ln(price) (5)	Ln(qap) (6)	Ln(quality) (7)	Ln(emargin) (8)
Ln(1+USStar)	0.129*** (0.01)	-0.342*** (0.05)	0.478*** (0.05)	0.006*** (0.00)	0.129*** (0.01)	-0.455*** (0.05)	0.589*** (0.05)	0.009*** (0.00)
Ln(1+USStar) × GDPcapRatio					-0.521*** (0.05)	1.468*** (0.34)	-1.987*** (0.35)	-0.056*** (0.01)
Ln(1+USStar) × GDPRatio					-1.698*** (0.36)	9.408*** (2.46)	-11.088*** (2.51)	-0.407*** (0.09)
Ln(1+USStar) × Ln(Dist)					0.017 (0.03)	2.828*** (0.16)	-2.811*** (0.16)	-0.027*** (0.01)
Ln(1+USStar) × ImpGrowth					-0.013 (0.02)	0.198** (0.09)	-0.215** (0.09)	0.001 (0.00)
Constant	2.113*** (0.00)	2.182*** (0.01)	-0.029*** (0.01)	0.147*** (0.00)	2.125*** (0.00)	2.200*** (0.01)	-0.037*** (0.01)	0.149*** (0.00)
Fixed effects	+	+	+	+	+	+	+	+
Adj. R ²	0.824	0.216	0.081	0.660	0.822	0.214	0.081	0.665
N	7736545	7444040	7444040	7736545	7156397	6896993	6896993	7156397

Note: The sample is the same as in Table 2. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled, and robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(2) Moving down the quality ladder of destinations

One may be immediately wondering that the quality upgrading in third markets should be more significant in poorer countries as the quality gap between Chinese exports to the US and to poorer countries should be larger. To further show the cross-country heterogeneity in the unit value, quality-adjusted price, and quality of Chinese exports w.r.t the US tariffs, we estimate the specification (2) by including the interaction terms of destination indicators and the US tariffs, and plot the destination-specific estimates of the US tariffs on three dependent variables in Figure 3 against the (ln) real GDP per capita ratio of the destination (relative to the US) in 2016.

We find that the quality upgrading of Chinese products exported to third markets is more pronounced in poorer countries, as suggested by the negative relationship between the elasticity of the quality w.r.t the US tariffs and the destination income level in panel C of Figure 3. Meanwhile, consistent with our previous finding that China diverts more of its exports to the South, we find that the supply effect of the trade diversion is also stronger in those countries, as indicated by the positive relationship between the elasticity of the quality-adjusted price w.r.t to the US tariffs and the destination income level in panel B of Figure 3. Overall, the quality upgrading effect increasingly dominates the supply effect of trade diversion in poorer countries, leading to a positive relationship between the elasticity of Chinese export prices to third markets w.r.t to the US tariffs and the destination income level in panel A of Figure 3.

Based on those observations, we include in regressions the interactions of the US tariffs with the destination's relative income (real GDP per capita ratio in 2016), relative size (real GDP ratio in 2016), the log distance to China, and HS4 sectoral annual import growth in the destination market as we did in column (3) of Table 2. All the variables for country characteristics are demeaned before taking the interactions. As shown in columns (5)-(7) in Table 4, the coefficients of the interaction between the US tariffs and the real GDP per capita ratio in the destination market on unit value, quality-adjusted price, and quality

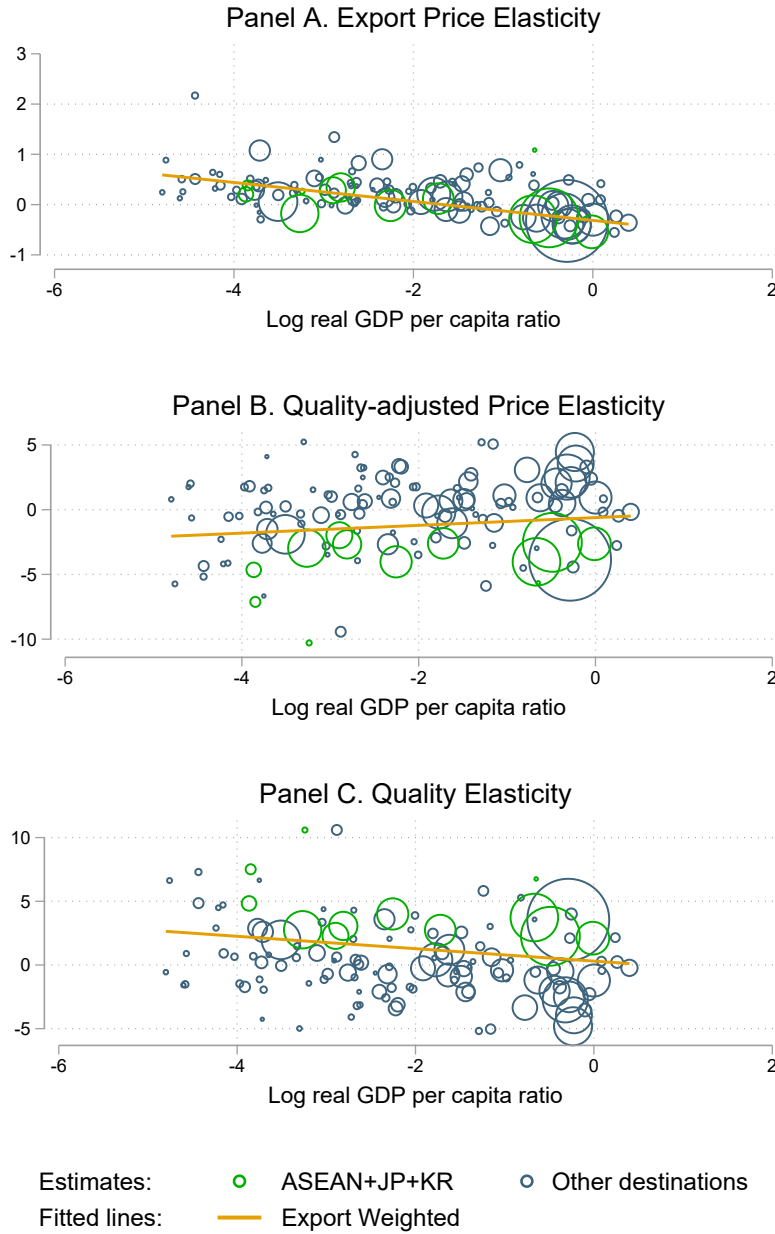


Figure 3: The destination-specific elasticity of price and quality

Note: Figure plots the estimated destination-specific price (quality-adjusted price/quality)-tariff elasticities over the destination's relative income level (to the US). The elasticities are obtained from a regression of log export price (quality-adjusted price/quality) on the tariff variable interacted with destination dummies, where product-month, destination-sector, and destination-time fixed effects are included, i.e., $\ln Y_{ckt} = \gamma_0 + \sum_i \gamma_i \ln(1 + \tau_{kt}^{US}) \times \mathbb{I}\{i = c\} + \alpha_{km} + \alpha_{ct} + \alpha_{ch} + \varepsilon_{ckt}$. Fitted lines are weighted by bilateral exports to each destination in 2016, and weights are indicated by the sizes of circles.

Table 5: Cross-country heterogeneity in trade diversion

	Averaged income country	Poor country A	Response difference
% changes of:	(1)	(2)	(3)=(2)-(1)
Qap	-4.55	-6.02	-1.47
Quality	5.89	7.88	1.99
Price	1.29	1.81	0.52
Quantity	2.43	3.19	0.76
Export value	3.72	5.00	1.28

Note: "Poor country A" is a hypothetical Southern country A (e.g., Poland) whose income (relative to the US) is 10 percentage points lower than the sample average income (e.g., Greece). The numbers show the percentage changes in different export diversion margins as a response to a uniform 10 percent US tariff rate hike.

reconfirm our findings in Figure 3.

To compare the magnitudes of trade diversion and quality upgrading across destinations with different incomes, we consider a uniform 10 percent US tariff hike and compute the responses of different margins of exports diversion in an average income country (e.g., Greece) and a hypothetical Southern country A (e.g., Poland) whose relative income is 10 percentage points lower than the sample average. The results are presented in Table 5. The increase in the export quantities of Chinese products diverted to Country A will be 0.76 pp higher than the average increase of export quantity diversion of 2.43%, and this depresses the quality-adjusted price in country A by 1.47 pp more than the average quality-adjusted price change of -4.55%. However, the increase in quality of products diverted to country A will be 1.99 pp higher than the averaged quality upgrading effect of 5.89%, and thus the increase in export price in country A will be 0.52 pp higher than the average price hike of 1.29% in third markets, meaning that the quality upgrading dominates the supply effect on export prices. Overall, the increase in the export diversion to country A will be 1.28 pp higher than the average increase of export diversion of 3.72%.

Moreover, we find that the quality upgrading effect and the supply effect due to trade diversion are stronger in countries with smaller sizes and closer to China. This is reasonable as those markets have high exposure to the trade diversion of Chinese products. In addition, high import demand in third markets helps to mitigate the competition due

to the supply effect but does not lead to more quality upgrading in their imports from China.

(3) Extensive margin

We also adopt the same regressions for the logarithm of extensive margin measured as the number of HS8 varieties within each HS6 category that China exports to third markets. Consistent with our expectation, columns (4) and (8) in Table 4 show that the trade diversion has positive effects on the extensive margin of Chinese exports to third markets, indicating that Chinese exporters introduce new product varieties into other countries upon the outbreak of the trade war.¹⁰ Moreover, this positive effect is stronger in countries with lower income, smaller market size, and closer to China, which are exposed to more trade diversion as we have shown previously. This suggests that the penetration cost (marketing cost for new products) might be lower in those destinations due to the quality advantage of Chinese products previously sold in the US.

(4) Cross-product-heterogeneity in quality scope

Recent studies have shown that export products have various quality scopes or lengths of product quality ladder (Khandelwal, 2010; Fan et al., 2015; Flach and Unger, 2022). For example, differentiated products usually have larger variations in quality than homogeneous products. Thus, vertical trade diversion is more likely to occur for products with high quality scope. To test this possibility, following the literature we construct three different indicator variables of high quality scope for each HS6 product and interact each of them with the US tariffs. Next, we include these interactions one by one in the regression in column (7) of Table 4 where quality is the dependent variable. If the quality upgrading in third markets is more significant for products with high quality scope, we should expect the estimated coefficients of those interaction terms to be positive.

¹⁰This result is consistent with Li et al. (2022)'s finding that Chinese exporters put more effort into searching for new markets for their products upon the US tariff shocks.

The first popular measure of quality scope (HQS^{Rauch}) is an indicator variable for differentiated goods according to Rauch's classification (Rauch, 1999), as differentiated products are considered to have higher product scopes than homogeneous products (Khandelwal, 2010; Fan et al., 2015; Flach and Unger, 2022).¹¹ The second indicator ($HQS^{Quality-SD}$) is based on the variation of the estimated quality for each HS6 product across countries. Based on the product-country-month-level quality estimated on the sample of Chinese exports to the US and all other 131 countries in 2017, we compute the standard deviation of estimates of quality for each HS6 product and classify those products to the group with high quality scope if their standard deviations of quality estimates are above the sample median, and the rest belongs to the group with low-quality scope. The instinct behind this measure is that if the estimated quality is of greater volatility within a specific product, this product tends to have a higher quality scope.

Thirdly, as the industry-level R&D intensity has been widely used to measure the quality differentiation (Kugler and Verhoogen, 2012; Bernini and Tomasi, 2015; Manova and Yu, 2017; Fan et al., 2018; Flach and Unger, 2022), our third indicator for high quality scope (HQS^{RD-SD}) is based on the variations of R&D intensity across firms within the same 4-digit industry according to the Chinese industrial classification (CIC4). More specifically, we define the R&D intensity as the ratio of R&D expenditure relative to the firm's total assets, using the information from Chinese annual surveys of manufacturing enterprises in 2013, and compute the standard deviation of R&D intensity across firms for each industry. Thus, a HS6 product is classified into the group with the high quality scope if its corresponding industrial standard deviation of R&D intensity is above the median.¹² Among those three measures of high quality scope, we slightly prefer the third one as it captures the variations in the quality of Chinese products more reliably and more directly

¹¹Specifically, we classify HS6 products as differentiated products if their corresponding 4-digit SITC classification is coded as differentiated products under Rauch's conservative classification, otherwise as homogeneous products.

¹²We manually construct the concordance between HS6 (version 2017) and CIC4 (version 2011) through ISIC rev 4 and NAICS/US 2017.

than the other two measures as it uses the additional information of R&D intensity of Chinese manufacturing enterprises.

Next, we extend the econometric specification in column (7) of Table 4 by including the interactions of three indicator variables for high quality scope with the US tariffs. Columns (1)-(3) in Table 6 show that all these three interaction terms are significantly positive, indicating that the quality upgrading for Chinese products that are diverted from the US to the third country due to the US tariffs are more significant for the products with high quality scope. According to our preferred measure of high quality scope in column (3), with one percentage point increase in the US tariffs on Chinese exports, the changes in estimated quality of Chinese exports to third markets will be about 0.40 percent and 0.76 percent for the groups of products with low and high quality scopes, respectively.

Table 6: Heterogeneous quality scope

<i>Dependent Variable</i>	Ln(quality)			Ln(exp)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1+UStar)	0.532*** (0.05)	0.427*** (0.05)	0.404*** (0.05)	0.342*** (0.02)	0.281*** (0.02)	0.243*** (0.02)
Ln(1+UStar) × HQS ^{Rauch}	0.077* (0.05)			0.041* (0.02)		
Ln(1+UStar) × HQS ^{Quality-SD}		0.306*** (0.05)			0.168*** (0.02)	
Ln(1+UStar) × HQS ^{RD-SD}			0.352*** (0.05)			0.244*** (0.02)
Constant	-0.037*** (0.01)	-0.036*** (0.01)	-0.036*** (0.01)	10.547*** (0.00)	10.547*** (0.00)	10.547*** (0.00)
Control variables	+	+	+	+	+	+
Fixed effects	+	+	+	+	+	+
Adj. R ²	0.081	0.081	0.081	0.532	0.532	0.532
N	6896993	6896993	6896993	7156397	7156397	7156397

Note: The sample is the same as in Table 2. The control variables include four interactions of US tariffs with the relative GDP per capita ratio, the relative GDP ratio, the distance between the destination capital and China, and the import growth in the destination market. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled, and robust standard errors clustered at the country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In columns (4) to (6) we replace the dependent variable (ln) quality with the log value of Chinese exports to the third country. The results show that trade diversion is also more

significant for the group of products with high quality scope than the other products. Based on column (6), with one percentage point increase in the US tariffs on Chinese exports, the increases in Chinese exports to third markets will be about 0.24 percent and 0.49 percent for the group of products with low and high quality scopes, respectively, providing additional supports to the vertical trade diversion.

Lastly, our previous results in Table 4 show that quality upgrading of Chinese exports in third markets is more significant in low-income countries by using the full sample of Chinese products exported to third markets. We expect that those results should also hold for the sub-sample of the products with high quality scope. Thus, we rerun the regression in column (7) of Table 4 for the sub-sample by using three different indicators of high quality scope. The first three columns of Table B.1 show that the results are largely consistent with the pattern we discovered in the full sample as shown in column (7) of Table 4, which is copied in the last column for easy comparison. Moreover, the fact that the quality upgrading in low-income countries is more significant is also more prominent for the products with high quality scope than the full sample, as indicated by the comparison of the coefficients of the interaction terms of the US tariffs and the demeaned relative income of third markets in columns (1)-(3) and the last column.

(5) Firm ownership

Exporters with different types of ownership may react to tariff shocks differently (Tian et al., 2022). For example, state-owned enterprises (SOE) might be used as an additional tool by the Chinese government to achieve some political goals (Benguria and Saffie, 2021), while foreign-invested firms (FIE) may have more flexibility in global reallocation due to their extensive global production networks. More importantly, firms with different ownership may have different vertical product differentiation and quality scopes, and therefore they may have different rooms in quality adjustments and trade diversion upon the US tariff shocks. In fact, Chinese export data at the firm-product level in 2016 shows

that FIEs concentrate more on high quality scope products based on the R&D intensity than SOEs and POEs, as 59 percent of FIE exports are high quality scope products while this statistic is only 48% and 40% for POEs and SOEs, respectively.

As firm ownership information in our trade data during 2017-2019 is unavailable, we could not slit the sample by firm ownership. Thus, we take an alternative approach similar to [Benguria and Saffie \(2021\)](#). Based on the firm-product level export data in 2016, we construct product-level export shares of three types of firms: SOE (state-owned and collective-owned enterprises), FIE (wholly-foreign-owned and joint ventures), and POE (private-owned enterprises and others), denoted by $SOEshr$, $FIEshr$, and $POEshr$ respectively. We include the interaction terms of US tariffs with $SOEshr$ and $FIEshr$ in our baseline specification in column (3) of Table 2, treating POEs as the baseline firm type.¹³

Table 7 reports the regression results and two interesting findings emerge. First, the vertical trade diversion patterns remain held. For a typical product with average shares of three types of firms ($SOEshr=0.12$, $FIEshr=0.32$ and $POEshr=0.56$), the elasticities of export value, unit price, quality-adjusted price, and quality w.r.t. the US tariffs are 0.375, 0.140, -0.460 and 0.606, respectively, which are on par with our baseline estimates in Table 2 and 4. These estimates indicate that a typical product sold in third markets upon a 10 percent US tariff shock will have a 3.8 percent increase in export value and a 6.1 percent increase in quality level.

Second, it also shows substantial heterogeneity in trade diversion and quality upgrading across firm ownership. Compared with POEs, SOEs are less market-driven, as the trade diversion and quality upgrading upon the US tariff shocks are substantially lower for SOEs. This is consistent with [Benguria and Saffie \(2021\)](#) that SOEs may bear additional policy burden from the Chinese government. By contrast, the positive coefficients of the tariff shocks and the interaction between the US tariffs and $FIEshr$ in columns (1) and (4) indicate that the trade diversion and quality upgrading pattern are more significant for

¹³Note we do not demean those export shares of firm ownership for easy interpretation.

Table 7: Firm ownership

<i>Dependent Variable</i>	Ln(exp)	Ln(price)	Ln(qap)	Ln(quality)
	(1)	(2)	(3)	(4)
Ln(1+UStar)	0.301*** (0.03)	0.290*** (0.02)	-0.351*** (0.07)	0.652*** (0.08)
Ln(1+UStar) × SOEshr	-0.514*** (0.10)	-0.258*** (0.05)	0.781*** (0.17)	-1.051*** (0.19)
Ln(1+UStar) × FIEshr	0.424*** (0.05)	-0.373*** (0.03)	-0.635*** (0.16)	0.250 (0.17)
Constant	10.547*** (0.00)	2.124*** (0.00)	2.200*** (0.01)	-0.037*** (0.01)
Control variables	+	+	+	+
Fixed effects	+	+	+	+
Adj. R ²	0.532	0.822	0.214	0.081
N	7155552	7155552	6896307	6896307

Note: The sample is the same as in Table 2. *SOEshr* and *FIEshr* are the HS6 product-level exporting shares by exporters' ownership types, where *SOE* denotes the "State-Owned Enterprises" and *FIE* denotes "Foreign-Invested Enterprises", based on the detailed firm-level trade data in 2016. Regressions include interaction terms of four control variables (the relative GDP per capita ratio, the relative GDP ratio, the distance between the destination capital and China, and the import growth in the destination market). HS6-Month, Country-HS2 and Country-Time fixed effects are controlled, and robust standard errors clustered at the country-product level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

FIEs than POEs, consistent with the fact that FIEs are concentrated more in high quality scope products. Note as the trade diversion is more significant for products with high FIE shares, the quality-adjusted price also drops more for those products, which largely offsets the positive effect of quality upgrading on export prices of those products in third markets.

(6) Political relationship and trade policy uncertainty

While we argue that the quality advantage of Chinese exports previously sold in the US makes them easier to penetrate the South, another possible explanation is the precautionary motive of Chinese exporters to avoid the political risk in the US allies. Chinese exporters may be worried that the U.S. allies may follow the US trade policy and impose

trade barriers on Chinese products. Therefore, to strategically avoid over-dependence on the US allies' markets, many of which are advanced economies, Chinese exporters may prefer diverting more to other low-income countries. Thus, we construct measures of political relationship and trade policy uncertainty to ensure that our results are robust to the control of political risks.

A standard data source for constructing measures of bilateral political distances is the votes in the United Nations General Assembly (UNGA), as the pattern of those votes is strongly correlated with alliances and similarity of economic and geopolitical interests (Alesina and Dollar, 2000). Thus, we measure the bilateral political distances between a third country and the US or China ($IPdist^{US}$ and $IPdist^{CN}$, respectively) by taking the absolute distance between the ideal points of two countries, estimated from the state-of-art method developed by Bailey et al. (2017). A higher value of $IPdist^{US}$ (or $IPdist^{CN}$) indicates that the third countries are politically more alienated from the US (or China).¹⁴ Next, we construct the changes in trade policy uncertainty index (ΔTPU) from Ahir et al. (2022), which covers 143 economies on a quarterly basis from 1996 onward, based on textual analysis on quarterly Economist Intelligent Unit (EIU) country reports.¹⁵

Next, we include the interaction term of US tariffs with the (demeaned) political distances between the third market and the US or China ($IPdist^{US}$ or $IPdist^{CN}$ respectively), and with the (demeaned) ΔTPU in the third market in the baseline specification alternatively. Table 8 shows that our baseline results are robust to controlling for political relationships and trade policy uncertainty, yet the magnitudes change slightly. Upon the US tariff hikes, Chinese exporters diverted their exports more to the South and upgraded the qualities of their products simultaneously.

More interestingly, we find that China indeed diverted less to US allies and more to its foreign friends. Column (1) in panel A of Table 8 indicates that upon a 10% US tariff hike, China would increase its exports by 4.19% on the averaged third market, but only

¹⁴Please see the data source and the construction method in the online Appendix B.5.

¹⁵See Appendix A.6 for the construction of the trade policy uncertainty index.

Table 8: Political distance and Trade policy uncertainty in VTD

<i>Dependent variable</i>	Ln(exp)	Ln(price)	Ln(qap)	Ln(quality)
	(1)	(2)	(3)	(4)
<i>Panel A. Political distance to US</i>				
Ln(1+UStar)	0.419*** (0.02)	0.139*** (0.01)	-0.534*** (0.05)	0.678*** (0.05)
Ln(1+UStar) × GDPcapRatio	-0.660*** (0.11)	-0.347*** (0.06)	1.083*** (0.40)	-1.423*** (0.41)
Ln(1+UStar) × IPdist ^{US}	0.401*** (0.04)	0.103*** (0.02)	-0.331*** (0.12)	0.436*** (0.13)
Adj. R ²	0.532	0.824	0.215	0.078
N	6946854	6946854	6706437	6706437
<i>Panel B. Political distance to China</i>				
Ln(1+UStar)	0.410*** (0.02)	0.137*** (0.01)	-0.527*** (0.05)	0.668*** (0.05)
Ln(1+UStar) × GDPcapRatio	-0.873*** (0.11)	-0.392*** (0.06)	1.206*** (0.40)	-1.594*** (0.41)
Ln(1+UStar) × IPdist ^{CN}	-0.348*** (0.05)	-0.099*** (0.03)	0.343** (0.17)	-0.442*** (0.18)
Adj. R ²	0.532	0.824	0.215	0.078
N	6946854	6946854	6706437	6706437
<i>Panel C. Trade policy uncertainty</i>				
Ln(1+UStar)	0.266*** (0.02)	0.110*** (0.01)	-0.210*** (0.06)	0.323*** (0.06)
Ln(1+UStar) × GDPcapRatio	-1.162*** (0.11)	-0.531*** (0.06)	1.530*** (0.39)	-2.052*** (0.40)
Ln(1+UStar) × ΔTPU	-0.019*** (0.00)	-0.008*** (0.00)	0.032** (0.01)	-0.041*** (0.01)
Adj. R ²	0.554	0.848	0.250	0.123
N	4407208	4407208	4260867	4260867

Note: The sample for Panel A and Panel B consists of all countries in Table 2 with political distance indices available. And the sample for Panel C consists of all countries in Table 2 with World Trade Uncertainty Index (WTUI) available. The political distances between the third market and the U.S. or China in 2016 ($IPdist^{US}$ or $IPdist^{CN}$ respectively), are from Bailey et al. (2017). ΔTPU measures monthly changes in the smoothed averages of Ahir et al. (2022)'s WTUI. We demean those variables before taking interactions with US tariffs. Same as previous regressions in Column (3) of Table 2 and Columns (5)-(7) of Table 4, we also included the constant, $Ln(1+UStar) \times GDPRatio$, $Ln(1+UStar) \times Ln(Dist)$ and $Ln(1+UStar) \times ImpGrowth$, as well as HS6-Month, Country-HS2 and Country-Time fixed effects. Robust standard errors clustered at the country-product level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

by 0.42% to a country that is one standard deviation closer to the US in terms of political distance. Similarly as shown in Panel B of Table 8, if a country is one standard deviation closer to China in terms of the political distance, Chinese exporters would expand their exports by 6.4%, which is 2.3 pp higher than the average of 4.1%. The results are similar if we replace the export value with the quantity. Moreover, Panel C of Table 8 suggests that the increase in trade policy uncertainty in the third markets tends to reduce export diversion.

(7) Tariff evasion through entrepôt trade

One may be wondering that Chinese exporters may take a detour through a third market to avoid the US tariffs. For example, Chinese exporters may export to Vietnam first and relabel their products as made-in-Vietnam for export to the US. Although it is difficult to assess the scale of such fraudulent certificates of origin, anecdote news media reported such activities. However, such tariff evasion is also very costly as it needs to pay the additional shipping costs, fraudulent certificates of origin, and possible punishment from the customs. Thus, Chinese exporters may strategically choose third countries for entrepôt trade if such activities exist. Below we propose two approaches to control possible tariff evasion activities.

First, Chinese exporters may choose third markets which have signed free trade agreements with the US for entrepôt trade, because they do not need to pay for high US tariffs, but in addition, they can also enjoy preferential tariffs when re-exporting to the US. Thus, we exclude countries that have free trade agreements with the US in regressions.¹⁶ The Panel A result in Appendix Table B.2 suggests that our main results still hold.

Second, in theory, it is possible for Chinese firms to export to the US through multiple third countries, but this strategy is less feasible as the rising shipping costs may signif-

¹⁶The US has free trade agreements in force with 20 countries in 2018: Australia, Bahrain, Canada, Chile, Colombia, Costa Rica, Dominican Republic, El Salvador, Guatemala, Honduras, Israel, Jordan, Korea, Mexico, Morocco, Nicaragua, Oman, Panama, Peru, Singapore.

icantly erode the potential benefits of tariff evasion. Thus, in practice, it is more likely that Chinese exporters will take one country for re-exporting to the US. In this case, we would observe both increases in Chinese exports to this country and US imports from it for the targeted products. Thus, we exclude those suspicious countries to check the robustness of our results. More specifically, we cross-referenced the top 20 country list with the largest increases in Chinese exports and the top 20 country list with the largest increases in U.S. imports of products subject to U.S. tariffs and found that nine countries appeared in both lists.¹⁷ After dropping the samples of those suspicious entrepôts, our Panel B results in Appendix Table B.2 remain supportive of our baseline findings. Admittedly, both approaches do not perfectly exclude the potential tariff evasion activities, but these two robustness checks may suggest that our vertical trade diversion is not driven by tariff evasion.

(8) Dynamics of vertical trade diversion

One may be wondering whether the effects of the US tariffs on trade diversion and quality upgrading are temporary or persistent. To address this question, we adopt a dynamic DID approach similar to Fajgelbaum et al. (2020) and plot the estimated coefficients in Figure 4. As a result, we find that before the announcement of the US tariffs on Chinese exports, there are no systematic differences in the trends of export values and quality between those targeted Chinese products and non-targeted Chinese products sold to other countries. After the announcement of the US tariffs which is roughly three months before the tariff enactment, both the diverted export value and quality have been steadily increasing, indicating the existence of announcement effects. Note this does not necessarily contradict our finding of the no-anticipation effects of the US tariffs on Chinese exports to the US in Appendix B.1. Because upon the announcement of the US tariffs, Chinese exports to the US may not decline immediately as the trade contracts have been ordered a

¹⁷They are Vietnam, Mexico, Korea, Thailand, Germany, Malaysia, Canada, Cambodia, and Singapore.

few months ago. However, the announcement of the US tariffs may lead to an immediate decline in future orders from US consumers and Chinese exporters then start exporting to other countries. This positive announcement effect suggests that our regression results on trade diversion and quality upgrading are rather conservative.

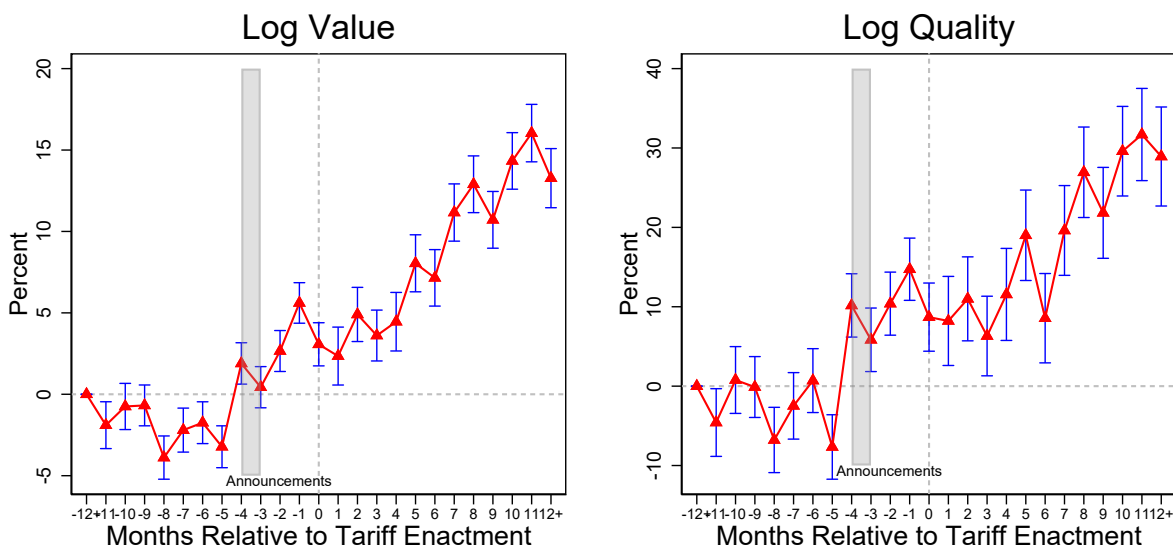


Figure 4: The dynamics of vertical trade diversion

Note: Figure plots the estimates of event time dummies for targeted products relative to untargeted products, obtained from the specification: $\ln Y_{ckt} = \sum_{h=-12}^{11} \delta_h^1 \mathbb{I}[T_{kt} = h] + \delta_{12+}^1 \mathbb{I}[T_{kt} \geq 12] + \sum_{h=-12}^{11} \delta_h^2 \mathbb{I}[T_{kt} = h] \times X_c + \delta_{12+}^2 \mathbb{I}[T_{kt} \geq 12] \times X_c + \alpha_{km} + \alpha_{ct} + \alpha_{ch} + \varepsilon_{ckt}$. The control variables (X_c) and fixed effects ($\alpha_{km/ct/ch}$) are the same as in Column (5) of Table 4. The “relative time”, $T_{kt} \triangleq t - E_k$, indicates the monthly periods since the product-level event time E_k . The observations of targeted products with $T_{kt} < -12$ are dropped, and those with $T_{kt} \geq 12$ are binned to a combined period. Standard errors are clustered at the country-product level. Error bars show 95% confidence intervals.

Moreover, Figure 4 also shows that the trade diversion and the associated quality upgrading in third markets become more significant about five and six months after the implementation of the US tariffs, indicating the existence of adjustment costs for export reallocation. Exporters may still engage in their pre-war orders for the US buyers due to the nature of long-term contracts even after implementing additional US tariffs. Thus, their production capacities could only be released slowly over time. In addition, it also takes time for marketing and establishing new trade networks in third markets.

(9) Summary remarks

In this section, we have provided extensive evidence to support the argument that China adopted the VTD strategy rather than the HTD strategy. Here we summarize the possible driving forces for Chinese exporters to adopt the VTD strategy. First, Chinese exporters face intense competition in advanced countries for high-quality goods. Thus, expanding the market share in the North may incur substantial marketing costs to attract more consumers. By contrast, when turning to the Southern market, Chinese exporters' marketing cost of high-quality products previously sold in the US may be relatively low due to the reputation and the quality advantage. Second, as we show in subsection (6) above, China diverted less to US allies, many of which are advanced economies. Thus, foreign political risk also partially reshaped Chinese exporters' trade diversion toward the South. Lastly, anecdotal news reports also suggest that Chinese local governments provide various support including information sharing, training, and export exhibition opportunities to exporters, which may help to reduce the costs of marketing and penetration to new markets.

V. Robustness check

V.A. Alternative explanations for export price adjustments

The key evidence supporting the vertical trade diversion is the positive effect of the US tariffs on the export prices of Chinese products shipped to other countries, as shown in Table 4. However, as the FOB export prices are measured by the unit value, which may reflect quality, unit cost, and markup (Lashkaripour, 2020), it is important to show that the effects of the US tariffs are through quality margin, rather than the alternative channels including markup and unit cost. Thus, below we show that both the markup and unit cost channels can not account for the positive effect of the US tariffs on the export

prices of Chinese products sold to other countries.

(1) Markup

Variable markups play a key role in cross-country price variations (Simonovska, 2015), and a flourishing literature studies firms' markup responses to changes in trade policy (De Loecker et al., 2016; Fan et al., 2018; Jung et al., 2019). Thus, it is important to rule out the possibility that Chinese firms raise their markup when they divert their exports to other countries upon the hike of the US tariffs.

Theoretically speaking, the average markup for a particular product is largely determined by the market structure of the product (Edmond et al., 2015; De Loecker et al., 2020). If the market is perfect competition, firms have no rooms to adjust their markups as they are price-takers. By contrast, if firms are monopolists they have the market power to adjust their markups in a response to tariff shocks. Thus, we check whether the positive effects of the US tariffs on the export prices of Chinese products in third markets are higher for the products with higher market concentrations.

Specifically, we construct two export market concentration indices: the Herfindahl–Hirschman Index (HHI) and the Concentration Ratio of top 5 exporters (CR_5) for each HS6 product-destination market, by using the detailed annual firm-HS6 product-destination-level trade data in 2016 collected by General Administration of Customs of P. R. China. Note an increase in HHI or CR_5 generally indicates a decrease in competition and an increase of market power or average markup of firms.

Next, we include the (demeaned) market concentration indices and their interaction terms with the US tariffs in the regression of $\ln(\text{export price})$ in column (5) of Table 4. Three interesting results emerge as shown in Table 9. First, the positive average effects of the US tariffs on the export prices of Chinese products in third markets still hold when we control for market concentrations and their interactions, as evidenced by the robust positive estimates of the US tariffs in columns (1)-(4). Second, consistent with our expect-

tation, a high degree of market concentration is largely associated with the high prices of Chinese exports in third markets, as indicated by the estimates of market concentration indices in columns (1) and (3).

Table 9: Controlling for markups in vertical trade diversion

<i>Dependent variable</i>	Ln(price)			
	HHI		CR ₅	
<i>Markup measures</i>	(1)	(2)	(3)	(4)
Ln(1+UStar)	0.131*** (0.01)	0.139*** (0.01)	0.132*** (0.01)	0.135*** (0.01)
MktCon	0.227*** (0.01)	0.245*** (0.01)	0.372*** (0.01)	0.377*** (0.01)
Ln(1+UStar) × MktCon		-0.272*** (0.03)		-0.082*** (0.03)
Constant	2.122*** (0.00)	2.122*** (0.00)	2.122*** (0.00)	2.122*** (0.00)
Fixed effects	+	+	+	+
Adj. R ²	0.826	0.826	0.826	0.826
N	6916713	6916713	6916713	6916713

Note: The sample is the same as in Table 2. Two markup indices, *HHI* and *CR5*, measure the market competitiveness among Chinese exporters in the HS6-destination-specific market in 2016, both of which are demeaned before being added to the regressions. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled, and robust standard errors clustered at the country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The most important finding is that the estimates of the interaction terms of the US tariffs and market concentration indices in columns (2) and (4) are significantly negative. This result has two implications. First, the positive effects of the US tariffs on Chinese export prices in other countries are stronger for more competitive markets where the market concentration is low and Chinese exporters have limited ability to adjust their markup. This directly suggests that markup adjustment may not be the driving factor for the rising Chinese export prices in third countries upon tariff shocks. Second, facing the US tariffs Chinese exporters in highly concentrated third markets raise their prices less compared with those in more competitive markets. This suggests that Chinese exporters with

more market power tend to lower their markups when they divert their products to other countries. Both implications suggest that markup adjustment is not the channel for the positive effects of the US tariffs on Chinese export prices in third markets.

(2) Input costs

Next, we check whether the US tariffs raise input costs in China and thus the export prices of Chinese exports shipped to other countries. In general, the input cost includes costs of labor, capital, and intermediate inputs from domestic and international markets. [Chor and Li \(2021\)](#) show that the US tariff shocks led to a significant decline in income per capita and manufacturing employment in grid locations that are exposed to US tariff shocks most, by using the high-frequency night lights data. Moreover, to ease the negative impact of the US tariff shocks, the monetary authority in China adopted an expansionary monetary policy and the interest rates declined gradually during 2018 and 2019. Thus, labor and capital costs are less likely to be the factors that raise Chinese export prices in other countries.

As for intermediate inputs, although we do not have price information for domestic inputs, we have detailed import prices of intermediate inputs that China imported from the rest of the world at the HS6 product-country-month level. As domestic and import inputs are substitutes, there should be positive co-movement of their prices upon the US tariff shocks. Thus, we check how the Chinese import prices of upstream inputs responded to the downstream US tariff hikes.

The downstream tariff exposure for an upstream sector S should reflect the export-weighted tariff increases on its downstream sectors as well as the importance of these downstream sectors as its clients. Thus, we define the sector S 's downstream US tariff exposure index as: $Down_UStar_{St} = \sum_J \left[\omega_S^J \times \sum_{j \in J} \frac{exp_j^{US}}{output_j} UStar_{jt} \right]$, where $\omega_S^J = \frac{use_J^S}{output_S}$ is the fraction of sector S 's output that is used for the production of downstream sector

J , computed from the Chinese input-output table in 2017.¹⁸ The second summation is the sectoral weighted US tariffs where the weight for product j is the share of exports to the US of product $j \in J$ in the total sectoral output J in 2017. We assume the products in sector S face the same downstream US tariff shocks.

Next, we examine how the downstream US tariff hikes affect Chinese firms' import prices, by regressing the import prices on the downstream US tariff shocks. This regression also helps to address the question of whether the US tariffs on Chinese exports pass onto the prices of Chinese imports from other countries. We first narrow our sample of imported products to intermediate products only based on the classification of the Broad Economic Categories (BEC). The input-output linkages we use to build the tariff exposure index have an underlying assumption that the imported products are used to produce downstream products. Thus, it would be more accurate if we use the intermediate inputs sample for regression analysis.

Column (1) of Table 10 presents the simple OLS regression result, and it shows that the downstream US tariffs made Chinese importers lower their import prices from other countries. In column (2) we also include Chinese retaliatory tariffs on the imports from the US to control for possible import substitution effects (Bown and Crowley, 2007, 2010; Cheng et al., 2021). In column (3) we further control the market power of Chinese importers, by including the interaction term of the downstream US tariffs and the Herfindahl–Hirschman Index (HHI) of Chinese importers in the market narrowly defined by the HS6 product-sourcing country pair. Clearly, those additional controls do not alter our main results and their coefficients are insignificant.

Next, we also repeat the previous three regressions for all imported products and find that the imported input prices continue to fall significantly upon the downstream US tariff shocks, as shown in columns (4) to (6) of Table 10. The estimates are also very close to the previous sample of intermediate inputs. One percentage point increase in

¹⁸Appendix A.5 contains detailed information about the Input-Output Tables we use.

Table 10: The effects of US tariffs on Chinese upstream import prices

Dependent Variable Sample	Ln(Import price)					
	Intermediates Only			All Products		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(1+Down.UStar)	-0.013*** (0.00)	-0.013*** (0.00)	-0.013*** (0.00)	-0.013*** (0.00)	-0.013*** (0.00)	-0.012*** (0.00)
Ln(1+CNtar)		-0.017 (0.04)	-0.015 (0.05)		0.068** (0.03)	0.067* (0.03)
Ln(1+Down.UStar) × imp_HHI			-0.007 (0.02)			-0.005 (0.01)
Constant	2.657*** (0.01)	2.658*** (0.01)	2.678*** (0.01)	3.312*** (0.00)	3.308*** (0.00)	3.322*** (0.00)
Fixed effects	+	+	+	+	+	+
Adj. R ²	0.694	0.694	0.685	0.760	0.760	0.755
N	1273823	1273823	1244119	2163325	2163325	2116769

Note: The sample includes all monthly import records with the same 131 non-US trade partners as in the export-side analysis, to whom China's exports exceed \$500 million. The *down_tariff* is the industry-level tariff exposure from downstream US tariffs, weighted by the input-output linkages as in the 2017 China Input-Output table. The *cn_tariff* represents China's retaliatory tariffs on US products. The markup index, *imp_HHI*, measures the market competitiveness among Chinese importers in the import market of a HS6 product in 2016, which is demeaned before being added to the regressions. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled, and robust standard errors clustered at the country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

the US downstream tariffs will lead to about 0.013 percent of the decrease in Chinese import prices. Although the magnitude is small, it at least suggests that the downstream US tariffs do not increase the input costs for Chinese firms. Note the only difference in the full sample is that the coefficient of Chinese retaliatory tariffs on the US becomes positively significant, indicating that those tariffs may cost China a higher import price for substituting the US products, particularly for those non-intermediate inputs.

Thus, the changes in markup and input costs are less likely to be the driving factors for the rising export prices of Chinese products sold to other countries upon the US tariff shocks. This analysis further supports that quality upgrading is the key mechanism for the positive effects of the US tariffs on Chinese export prices in third markets.

V.B. Additional results on VTD

(1) Alternative substitution elasticities

Our measures of quality and the quality-adjusted price are estimated as the unobserved attributes of a product that appeal to consumers after controlling for its price, where the substitution elasticity, σ , plays a key role in the estimation process. The literature yields and employs various estimates of σ . [Ahmad et al. \(2020\)](#) summarizes and compares the estimates of elasticities at different aggregation levels across studies, and finds that the estimates vary considerably across various studies. Therefore, we further employ a more aggregated σ and another more disaggregated one to test the sensitivity of quality and VTD strategy. Specifically, we use a constant $\sigma = 5$, following [Fan et al. \(2015\)](#), and σ_{ck} varying across destination-HS4 sector level from [Soderbery \(2018\)](#). Table [B.3](#) shows that our findings on quality upgrading and quality-adjusted prices are insensitive to those alternative substitution elasticities.

(2) Full sample of Chinese non-US trade partners

To avoid possible bias from small trade values and low trading frequencies and obtain more accurate estimates of quality and quality-adjusted price, we exclude the small trade partners to which China exported less than 500 million USD in 2017 in the previous analysis of trade diversion. However, as shown in Table [B.6](#) in Appendix [B.5](#), our results on VTD still hold for the whole sample of Chinese non-US trade partners. Moreover, the magnitudes of key estimates are also close to the baseline results in Table [2](#) and [4](#).¹⁹

In the online Appendix, we conduct two additional robustness checks. First, processing exporters are often the affiliates of foreign firms and thus have limited control over the export prices and the destinations of their goods. Thus, we split the sample by pro-

¹⁹Our finding that Chinese exporters divert more to the South may run counter to the results in [Jiang et al. \(2022\)](#), where they find opposite results. In Appendix [\(5\)](#), we present the detailed comparison of our econometric approach and their graphic approach, and show that their country-group-averaged DID estimates of US tariff hikes on China's exports to each third market tend to inflate the weights of Chinese small trade partners, and their results do not stand still in a properly specified regression for the sample of all Chinese Non-US trade partners.

cessing and ordinary exports, and find that the VTD and quality upgrading remain to hold for two customs regimes but the magnitudes are smaller for processing exports than ordinary exports. Second, we also show that our baseline results on VTD are robust when we control for Chinese import tariffs in upstream industries.

VI. Conclusion

Our study shows that upon the US tariff shocks Chinese exporters successfully divert their products to the South along the quality ladders, rather than to the North which is similar to the US. This VTD strategy also leads to significant quality upgrading and export price increases in Chinese products diverted to the South despite the discounts in quality-adjusted prices, and thus helps to improve China's gross terms of trade in third markets.

This paper highlights the role of quality in trade diversion, which has been largely ignored in the literature, particularly in the multi-country multi-industry general equilibrium quantitative trade models that numerically evaluate the benefits and costs of the US-China trade war. Ignoring the quality margin in the model may lead to a biased estimation of the gains and losses from the trade war. Our study suggests that future quantitative studies should include the quality margin in those models such as [Feenstra and Romalis \(2014\)](#).

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Appendix

For Online Publication

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A Data and Variables

A.1 Third markets list

Table A.1: The 131 non-US trading partners to whom China exported more than 500 million USD in 2017

Afghanistan	Estonia	Liberia	Romania
Algeria	Ethiopia	Libyan Arab Jamahiriya	Russian Federation
Angola	Finland	Lithuania	Saudi Arabia
Argentina	France	Luxembourg	Senegal
Australia	Georgia	Macau	Serbia
Austria	Germany	Madagascar	Singapore
Bahrain	Ghana	Malaysia	Slovakia
Bangladesh	Greece	Malta	Slovenia
Belarus	Guatemala	Marshall Islands	South Africa
Belgium	Guinea	Mauritania	Spain
Benin	Haiti	Mauritius	Sri Lanka
Brazil	Honduras	Mexico	Sudan
Brunei	Hong Kong, China	Mongolia	Sweden
Bulgaria	Hungary	Morocco	Switzerland
Cambodia	India	Mozambique	Syrian Arab Republic
Cameroon	Indonesia	Myanmar	Taiwan, Prov.of China
Canada	Iran	Nepal, FDR	Tajikistan
Chile	Iraq	Netherlands	Tanzania
Colombia	Ireland	New Zealand	Thailand
Congo,DR	Israel	Nicaragua	Togo
Costa Rica	Italy	Nigeria	Tunisia
Cote d'Ivoire	Jamaica	Norway	Turkey
Croatia	Japan	Oman	Uganda
Cuba	Jordan	Pakistan	Ukraine
Cyprus	Kazakhstan	Panama	United Arab Emirates
Czech Republic	Kenya	Papua New Guinea	United Kingdom
Denmark	Korea, Rep.	Paraguay	Uruguay
Djibouti	Korea,DPR	Peru	Uzbekistan
Dominican Republic	Kuwait	Philippines	Venezuela
Ecuador	Kyrgyzstan	Poland	Viet Nam
Egypt	Lao PDR	Portugal	Yemen
El Salvador	Latvia	Puerto Rico	Zambia
Bolivia	Lebanon	Qatar	

A.2 Tariff shocks and trade data

Table A.2: Descriptive statistics: trade with US/R.o.W./World

Variable	Obs	Mean	Std. dev.	Min	Max
<i>Exports to US</i>					
Ln(exp)	130,570	13.16	2.930	0	22.42
Ln(quan)	130,570	10.97	3.677	-6.908	25.81
Ln(price)	130,570	2.186	2.358	-7.661	17.93
<i>Exports to R.o.W.</i>					
Ln(exp)	168,819	15.02	2.636	0	23.38
Ln(quan)	168,819	13.03	3.627	-6.215	26.47
Ln(price)	168,819	1.989	2.689	-7.973	20.05
<i>Exports to World</i>					
Ln(exp)	169,425	15.15	2.673	0	23.67
Ln(quan)	169,425	13.16	3.641	-6.215	26.47
Ln(price)	169,425	1.995	2.678	-7.973	20.05

Table A.3: Descriptive statistics: regression data with major countries

Variables	Obs.	Mean	Std. dev.	Min.	Max.
<i>Dependent Variables</i>					
Ln(exp)	7,738,372	10.56	2.67	0	22.58
Ln(quan)	7,738,372	8.44	3.60	-6.91	26.44
Ln(price)	7,738,372	2.12	2.49	-13.56	21.09
Ln(qap)	7,445,227	2.16	6.08	-143.61	207.59
Ln(quality)	7,445,227	0.00	5.81	-208.28	153.52
Ln(emargin)	7,738,372	0.15	0.35	0	3.26
Ln(imargin)	7,738,372	10.42	2.58	0	21.48
<i>Independent Variables</i>					
Ln(1+UStar)	7,738,372	0.06	0.09	0	0.34
GDPcapRatio	7,507,489	0.31	0.34	0.01	1.81
GDPRatio	7,545,432	0.03	0.05	0.00	0.24
Ln(Dist)	7,588,118	8.81	0.63	6.70	9.87
ImpGrowth	7,237,119	0.11	0.50	-1.00	2.99
ImpSI	7,588,118	0.55	0.11	0.04	0.76
ExpSI	7,588,118	0.54	0.14	0.01	0.85
IncSI ^l	7,507,489	-1.91	1.32	-4.80	0.00
IncSI ^o	7,623,081	0.61	0.18	0.23	0.91
HQS ^{Rauch}	7,738,372	0.77	0.42	0	1
HQS ^{Quality-SD}	7,738,372	0.53	0.50	0	1
HQS ^{RD-SD}	7,738,372	0.53	0.50	0	1
POEshr	7,568,848	0.56	0.21	0	1
SOEshr	7,568,848	0.12	0.12	0	1
FIEshr	7,568,848	0.32	0.21	0	1
HHI	7,297,973	0.33	0.28	0.00	1
CR ₅	7,297,973	0.79	0.23	0.05	1
Ipdist ^{US}	7,380,927	2.58	0.94	0.16	4.55
Ipdist ^{CN}	7,380,927	0.79	0.66	0.00	2.83
Δ TPU	4,681,774	0.18	2.42	-27.22	37.76

Note: The "major countries" are the 131 non-US countries to whom China exports with a value of greater than or equal to 500 million USD in 2017.

A.3 Income distribution similarity index

As mentioned before, we collect the average income levels of deciles in 2016 for each country from the World Inequality Database (WID.WORLD). s_c^d denotes the share of total income in country c which is earned by decile d , where $d \in \{1, 2, \dots, 10\}$. The computation of income distribution similarity index ($IncSI_c^o$) takes the following 4 steps:

1. **Transfer the average incomes of deciles for each country in 2016 into the comparable unit.** We choose the average of pre-tax national income among equal-split adults (coded as "aptinc992j") as our income index since it's the most widely used index and also the benchmark distributional income concept in the database. It includes social insurance benefits (and remove corresponding contributions), but exclude other forms of redistribution (income tax, social assistance benefits, etc.). The original income data is valued in local currency unit, thus we use the PPP exchange rate (coded as "xlcusp") to convert local currency unit into US dollar. We denote country c 's average income level of decile d as x_c^d .
2. **Redistribute the average incomes of deciles into income intervals.** By definition, each x_c^d has the area of 0.1 in the probability mass function of the discrete income distribution. Following the practice of [Bernasconi \(2013\)](#), we assume that the area of 0.1 of x_c^d is uniformly distributed on the interval $[\underline{x}_c^d, \bar{x}_c^d]$,

$$\underline{x}_c^d = \begin{cases} x_c^d - \frac{x_c^d - x_c^{d-1}}{2} & \text{if } d > 1 \\ x_c^{min} & \text{if } d = 1 \end{cases}$$

$$\bar{x}_c^d = \begin{cases} x_c^d + \frac{x_c^{d+1} - x_c^d}{2} & \text{if } d < 10 \\ x_c^{max} & \text{if } d = 10 \end{cases}$$

The x_c^{min} is set to 1 for all country c , and the x_c^{max} is approximated by the 100th

percentile. Observing the sample average of $\frac{x_c^{max} - x_c^{10}}{x_c^{10} - x_c^9} = 1.16$, we set $x_c^{max} = x_c^{10} + 1.16 * (x_c^{10} - x_c^9)$.

3. **Reshape the densities into common intervals with a length of 5000 USD.** The income intervals we obtain in the second step are not common across countries, so we uniform the income intervals into intervals with a step size of 5000 USD. The poorest country spans two intervals under the 5000 step-size, and the richest one spans 345 intervals. Using \hat{x} to denote discrete income intervals, we have $\sum_{\hat{x}} f_c(\hat{x}) = 1$, $\hat{x} \in \{[1, 5001), [5001, 10001), \dots, [1720000, 1725001)\}$ for all country c .
4. **Aggregate the overlap areas in each standardized interval.** With the densities for all countries partitioned into common intervals, we could get the income distribution overlap area of country c and the US by simply adding the overlap ratio of all standardized intervals,

$$IncSI_c^o = \sum_{\hat{x}} \min\{f_c(\hat{x}), f_{US}(\hat{x})\}$$

which is the discrete form of $IncSI_c^o = \int_x \min\{f_c(x), f_{us}(x)\} dx$.

A.4 Distributions of estimated quality

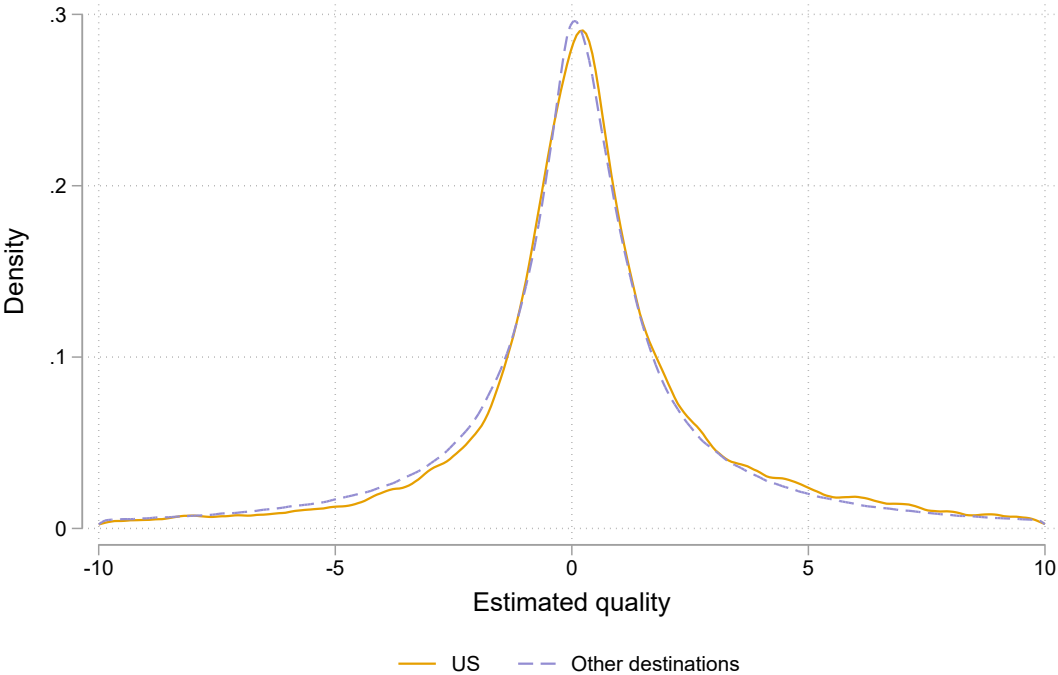


Figure A.1: Estimated quality of Chinese products exported to US and other destinations

A.5 Downstream/Upstream tariff exposures through input-output linkages

Data Sources. Besides China’s trade data and US tariff lists, two more sets of data are needed to construct downstream and upstream tariff exposure index, including:

1. The “use” table in Input-Output Tables of China 2017 (IOT2017) and the corresponding concordance between IOT2017 industries and HS2017 products. The National Bureau of Statistics of China would conduct a nationwide survey and release the input-output tables every 5 years. We use the latest version of 2017, which happens to be the year before the outbreak of the trade war. The “use” table we use includes three types of information. The first one is the intermediate use presented by a matrix with elements use_S^J —the value of products in (upstream) industry S used in the production of products in (downstream) industry J . The second part contains the final use of every industry, including detailed domestic final consumption and exports, as well as the imports and total outputs of every industry. The third part contains detailed value added of every industry, including the payment for labour, the net production tax, etc., as well as the total inputs of every industry. There are 149 industries in IOT2017 classified based on the Chinese industrial classification of 2017 (CIC2017). We thus manually construct the concordance between HS6 (version 2017) and IOT2017 through CIC and ISIC.
2. China’s retaliatory tariff lists. We collect the original tariff lists from the official website of Ministry of Finance of the People’s Republic of China. Similar to the US tariff lists, we weigh the original lists of HS-8 digit products into HS-6 digit products using China’s imports from the US in 2017.

China’s upstream tariff changes China’s upstream tariff exposure index is defined similarly to the downstream tariff exposure index, but with some adjustments to account for the labor as another input. Specifically, we define a (downstream) sector J ’s tariff

exposure from its upstream sectors as follows, which is similar to the concept of "rising input costs" as in [Flaen and Pierce \(2020\)](#):

$$\begin{aligned}
 Up_CNtar_{Jt} &= \sum_S \left[\overbrace{\frac{use_J^S}{\sum_{S \in \Omega_S} use_J^S + W_J}}^{S's \text{ importance as } J's \text{ input source}} \right. \\
 &\quad \times \underbrace{\frac{imps}{output_S + imps - exps}}_{S's \text{ import share in domestic absorption}} \times \left. \overbrace{\sum_{s \in S} \frac{imp_s^{US}}{imps} CNtar_{st}}^{\text{weighted tariff hike per RMB import of } S} \right] \\
 &= \sum_S \left[\frac{use_J^S}{\sum_{S \in \Omega_S} use_J^S + W_J} \times \underbrace{\sum_{s \in S} \frac{imp_s^{US}}{output_S + imps - exps} CNtar_{st}}_{\text{weighted tariff hike per RMB domestic absorption of } S} \right]
 \end{aligned}$$

where use_J^S is the fraction of sector S 's output that is used for the production of downstream sector J . $\sum_{S \in \Omega_S} use_J^S$ is sector J 's total intermediate inputs and W_J is its compensation of employees. So the first summation represents the input share of upstream sector S in the sum of all intermediate inputs and labors used by sector J . The second summation is the sector-level weighted retaliatory tariffs on China's imports from the US, where the weight for product s is the share of product s 's imports from the US in its corresponding sector S 's domestic absorption S , $output_S + imps - exps$, in 2017.

A.6 Political relationship and trade policy uncertainty

Measuring political relationship. A standard data source for constructing measures of country's political distances is the votes in the United Nations General Assembly (UNGA). [Alesina and Dollar \(2000\)](#) argue that UN votes are a reliable indication of the global political alliances between countries because the pattern of those votes is strongly correlated with alliances and similarity of economic and geopolitical interests. [Bailey et al. \(2017\)](#) proposed to use spatial models and item response theory empirical methods to estimate country's political orientation and bilateral political relations based on UNGA voting data. Unlike previous UN-based preference measures, such as [Signorino and Ritter \(1999\)](#)'s S score and [Gartzke \(2010\)](#)'s affinity index, their new estimation could distinguish agenda changes from preference changes and lessen the influence of idiosyncratic votes. This ideal points measure, which has been widely used by political economics researchers,¹ is a more accurate and robust indicator of inter-state preference similarity.

Based on [Bailey et al. \(2017\)](#)'s work, we measure the bilateral political distances between a third country and the US or China ($IPdist^{US}$ and $IPdist^{CN}$, respectively) by taking the absolute distance between country ideal points.² A higher value of $IPdist^{US}$ (or $IPdist^{CN}$) indicates that the third countries are politically more alienated from the US (or China).

Measuring trade policy uncertainty. Researchers have used different measures of TPU, which can be classified into two broad categories ([Handley and Limão, 2022](#)). One relies on textual analysis to identify certain terms related to TPU and construct time-varying indices.³ The other approach identifies potential events leading to a policy regime

¹See, for example, [Winters and Streitfeld \(2018\)](#), [Dreher et al. \(2019\)](#), [Clark and Dolan \(2021\)](#), [Cormier \(2022\)](#), and [Terman and Byun \(2022\)](#).

²Our data of country-level ideal point estimates are from [Voeten et al. \(2009\)](#)'s latest version of V29 published in June 2022.

³This "Index" family can be further separated into news-based indices (among those, [Baker et al. \(2016\)](#) and [Huang and Luk \(2020\)](#) are two of the representative studies) and company reports and investor conference calls-based indices (for example, [Hassan et al. \(2019\)](#), [Hassan et al. \(2020\)](#), and [Benguria et al. \(2022\)](#)).

switch, such as a trade agreement, and exploits policy variation to measure TPU.⁴

Considering that we need a TPU measure that is both time-varying and consistently estimated across countries, we refer to [Ahir et al. \(2022\)](#)'s World Trade Uncertainty Index to construct our TPU measure. They construct both World Uncertainty Index (WUI) and World Trade Uncertainty Index (WTUI) for 143 individual countries on a quarterly basis from 1996 onward based on textual analysis on quarterly Economist Intelligent Unit (EIU) country reports.

To better capture the monthly dynamics of TPU, we measure the changes of TPU as $\Delta TPU_{c,t} = WTUI_{c,t}^w - WTUI_{c,t-1}^w$, where $WTUI_{c,t}^w$ is a 3-month weighted moving average:

$$WTUI_{c,t}^w = 0.6 * WTUI_{c,t} + 0.3 * WTUI_{c,t-1} + 0.1 * WTUI_{c,t-2}$$

The weights of this smoothed index are the same as those used by [Ahir et al. \(2022\)](#) in their 3-quarter weighted moving averaged WUI.

⁴Representative researches include [Handley \(2014\)](#), [Handley and Limão \(2015\)](#), [Handley and Limão \(2017\)](#) and [Feng et al. \(2017\)](#).

B Supplemental Empirical Results

B.1 Event study: testing the Pre-trends of the US tariffs on Chinese exports to the US

In this section, we examine the direct effects of US tariffs on Chinese exports to US by using the Chinese monthly exports data at HS6 product level. We adopt the approach of the event study by using a multi-period Differences-in-Differences (DID) setting to show the dynamic average effects of the US tariffs on Chinese exports and the parallel trends for the levied products and non-levied goods. Similar to [Fajgelbaum et al. \(2020\)](#), we use the following specification:

$$\ln Y_{kt}^{US} = \sum_{h=-6}^{11} \delta_h \mathbb{I}[T_{kt} = h] + \delta_{12+} \mathbb{I}[T_{kt} \geq 12] + \alpha_{km} + \alpha_t + \epsilon_{kt} \quad (\text{B.1})$$

where Y_{kt}^{US} is the variable of interest such as the export value, quantity and unit price of Chinese product k shipped to the US at time year-month t . The "relative time", $T_{kt} \triangleq t - E_k$, indicates the periods since the product-level event date E_k . We exclude the earliest "pre-trend" period, $\mathbb{I}[T_{kt} = -6]$, as a normalization, following the practice of [Fajgelbaum et al. \(2020\)](#). The observations of targeted products with $T_{kt} < -6$ are dropped, and those with $T_{kt} \geq 12$ are binned to a combined period. α_{km} is the HS6 product-month fixed effects which capture the product-specific seasonal effects, and α_t is the year-month time fixed effects which capture the macroeconomic conditions of the importing and exporting countries. We also cluster the standard error at the HS6 product level, which is the finest level we can match the US tariffs and Chinese export data. We plot the $\hat{\delta}_h$ that captures the dynamic responses of the variables of interest to the US tariff shocks.

Figure [B.1](#) reports the dynamic average effects of the US tariff hikes on Chinese exports to the US. The top two panels show that the US tariffs significantly reduce Chinese exports both for the trade value and quantity. By contrast, the differences between the tar-

geted products and non-targeted ones before the tariff enactment are largely insignificant, indicating the trend similarity between products in treatment and control groups. Lastly, the tariffs do not have significant effects on the price of Chinese exported products sold to the US, consistent with previous studies showing that the US tariffs almost completely pass through to the US consumers ([Fajgelbaum et al., 2020](#); [Cavallo et al., 2021](#)).

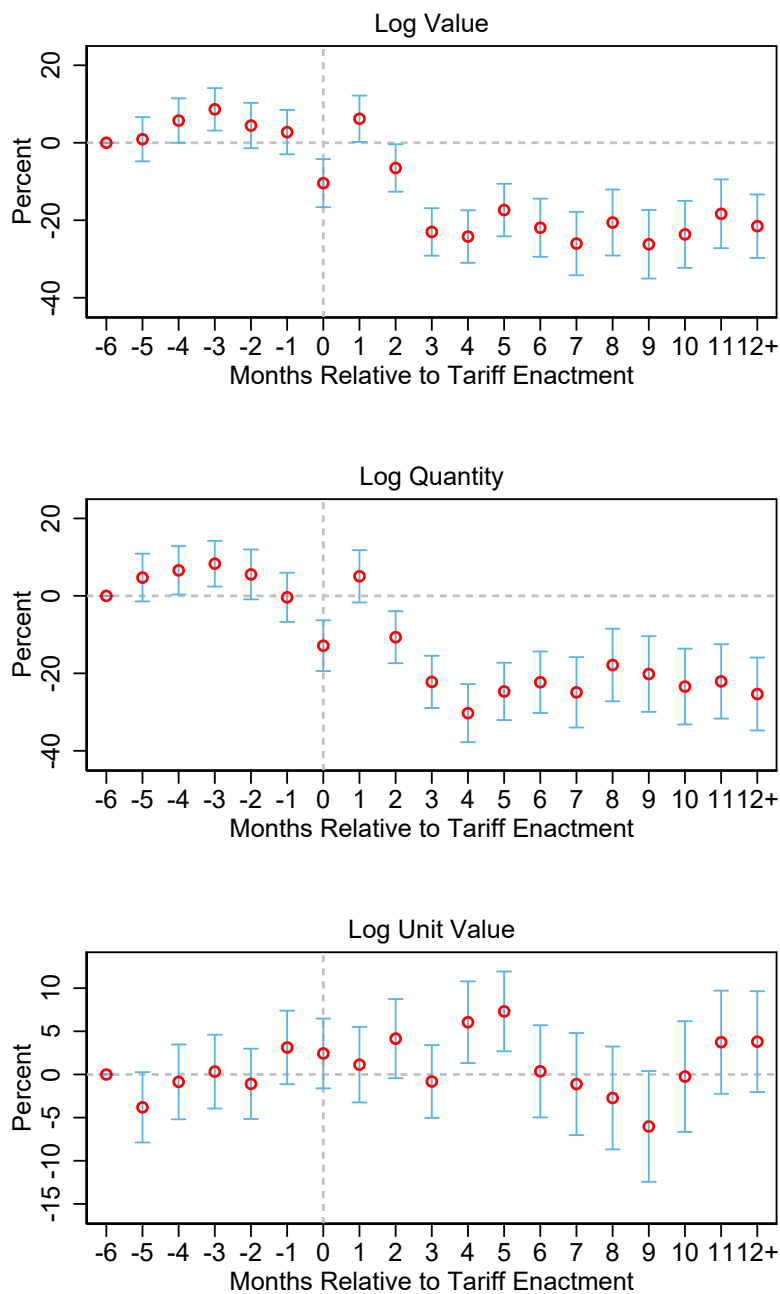


Figure B.1: The dynamic effects of the US tariffs on Chinese exports to US

Note: Figure plots event time dummies for targeted products relative to untargeted products, with the sample of Chinese exports to the US only. Regressions include product-month and time fixed effects. Standard errors are clustered by HS-6 products. Event periods before -6 are dropped, and event periods > 12 are binned. Error bars show 95% confidence intervals.

B.2 Export loss and diversion upon the US tariff shocks

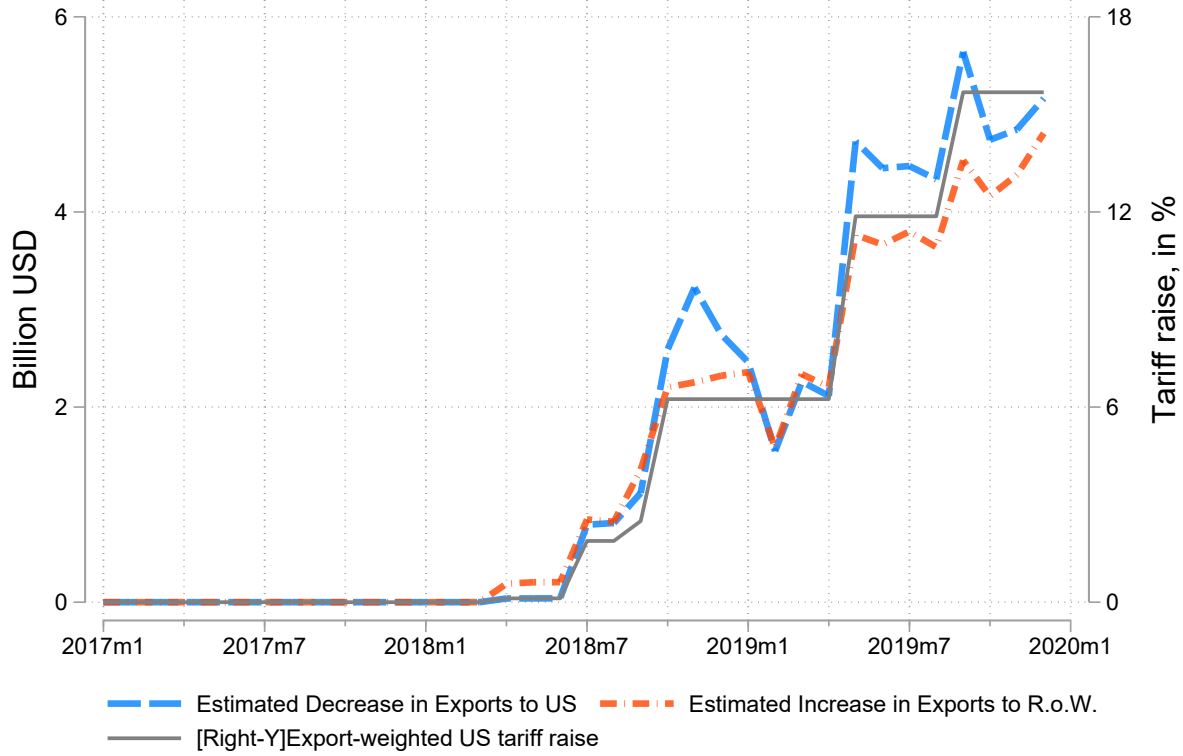


Figure B.2: Chinese export loss and diversion upon the US tariff shocks

Note: This figure plots the monthly export loss in China's exports to the US and export rise in China's exports to the rest of the world (excluding the US), using the estimated coefficients in Column (1) and Column (4) of Table 1, as well as the monthly tariff hike averaged with weights by China's exports to the US in 2017. Specifically, we use the estimated $\widehat{\beta}_0^d$, $\widehat{\alpha}_{km}^d$, $\widehat{\alpha}_t^d$, and $\widehat{\varepsilon}_{kt}^d$ to get the expected export value of product k at time t in the absence of external US tariffs, $\widehat{exp}_{kt}^d = e^{\widehat{\beta}_0^d + \widehat{\alpha}_{km}^d + \widehat{\alpha}_t^d + \widehat{\varepsilon}_{kt}^d}$, $d \in \{US, RoW\}$. And the gap between this expected export value and the actual export value, $\sum_k (exp_{kt}^d - \widehat{exp}_{kt}^d)$, is the export changes caused by US tariff shocks at time t in destination d .

B.3 Sub-sample regressions of products with high-quality scope

Table B.1: The subsample of products with high quality scope

<i>Dependent variable</i>	Ln(quality)			
	Rauch (1)	Quality_SD (2)	RD_SD (3)	- (7) in Tabel 4
Ln(1+UStar)	0.636*** (0.06)	0.697*** (0.09)	0.600*** (0.09)	0.589*** (0.05)
Ln(1+UStar) × GDPcapRatio	-2.532*** (0.42)	-3.011*** (0.57)	-2.480*** (0.56)	-1.987*** (0.35)
Ln(1+UStar) × GDPRatio	-13.144*** (3.15)	-14.436*** (4.22)	-16.997*** (4.15)	-11.088*** (2.51)
Ln(1+UStar) × Ln(Dist)	-3.305*** (0.20)	-3.940*** (0.28)	-3.356*** (0.27)	-2.811*** (0.16)
Ln(1+UStar) × ImpGrowth	-0.304*** (0.11)	-0.376** (0.17)	-0.518*** (0.17)	-0.215** (0.09)
Constant	-0.030*** (0.01)	-0.039** (0.02)	-0.034** (0.01)	-0.037*** (0.01)
Adj. R ²	0.084	0.100	0.086	0.081
N	5481606	3597131	3713598	6896993

Note: The sample is the same as in Table 2. Only high quality scope products are included in the regressions for Column (1) to (3), where high quality scope products are classified by measures listed in the second row. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.4 Sub-sample regressions by excluding entrepôt trade

Table B.2: Concerns on tariff evasions

<i>Dependent variable</i>	Ln(exp)	Ln(price)	Ln(qap)	Ln(quality)
	(1)	(2)	(3)	(4)
<i>Panel A. US FTA partners dropped</i>				
Ln(1+UStar)	0.337*** (0.02)	0.131*** (0.01)	-0.338*** (0.06)	0.475*** (0.06)
Ln(1+UStar) × GDPcapRatio	-1.531*** (0.11)	-0.483*** (0.06)	1.862*** (0.38)	-2.345*** (0.39)
Ln(1+UStar) × GDPRatio	-5.861*** (0.71)	-1.689*** (0.38)	8.886*** (2.56)	-10.556*** (2.62)
Ln(1+UStar) × Ln(Dist)	-0.898*** (0.06)	0.022 (0.03)	2.683*** (0.20)	-2.663*** (0.21)
Ln(1+UStar) × ImpGrowth	0.005 (0.03)	-0.022 (0.02)	0.150 (0.09)	-0.177* (0.10)
Adj. R ²	0.526	0.819	0.213	0.085
N	5852470	5852470	5647408	5647408
<i>Panel B. Potential entrepôts dropped</i>				
Ln(1+UStar)	0.406*** (0.02)	0.145*** (0.01)	-0.628*** (0.06)	0.779*** (0.06)
Ln(1+UStar) × GDPcapRatio	-1.325*** (0.10)	-0.501*** (0.06)	1.346*** (0.36)	-1.848*** (0.37)
Ln(1+UStar) × GDPRatio	-5.623*** (0.77)	-1.912*** (0.41)	7.828*** (2.72)	-9.753*** (2.78)
Ln(1+UStar) × Ln(Dist)	-0.994*** (0.06)	-0.062* (0.03)	2.771*** (0.20)	-2.836*** (0.20)
Ln(1+UStar) × ImpGrowth	-0.004 (0.03)	-0.003 (0.02)	0.187** (0.09)	-0.195** (0.09)
Adj. R ²	0.518	0.817	0.214	0.085
N	6231845	6231845	6025925	6025925

Note: Different with the sample used in Table 2, trade records with the 20 US FTA partners are excluded in Panel A, and those with the 9 potential entrepôts are excluded in Panel B. Constants are included in all regressions, and HS6-Month, Country-HS2 and Country-Time fixed effects are controlled. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.5 Robustness checks

(1) Alternative trade elasticities

The results are reported in Table B.3. In specification (1)-(2) and (5)-(6), we use $\sigma = 5$ for all products following the practice of Fan et al. (2015), which gives a sketchier estimation of quality, as well as quality-adjusted price. In specifications (3)-(4) and (7)-(8), we use the importer-HS4 level σ_{ck} based on the estimates of Soderbery (2018), a more dis-aggregated elasticity further considering the cross-country heterogeneity.

Table B.3: Vertical trade diversion under alternative trade elasticities

Dependent Variable	Ln(qap)			Ln(quality)						
	$\sigma=5$	(2)	(3)	σ_{cK}	(4)	(5)	$\sigma=5$	(6)	(7)	σ_{cK}
Ln(1+UStar)	-0.083*** (0.00)	-0.093*** (0.00)	-0.190*** (0.02)	-0.238*** (0.02)	0.211*** (0.01)	0.222*** (0.01)	0.299*** (0.02)	0.365*** (0.02)		
Ln(1+UStar) × GDPcapRatio	0.319*** (0.02)	1.058*** (0.20)	0.872 (1.65)	1.058*** (0.20)	-0.840*** (0.06)	-0.840*** (0.06)	-1.534*** (0.21)			
Ln(1+UStar) × GDPRatio	1.523*** (0.17)	0.872 (1.65)	0.403*** (0.11)	0.872 (1.65)	-3.220*** (0.41)	-3.220*** (0.41)	-2.489 (1.69)			
Ln(1+UStar) × Ln(Dist)	0.247*** (0.01)	0.247*** (0.01)	-0.093 (0.07)	0.403*** (0.11)	-0.230*** (0.03)	-0.230*** (0.03)	-0.387*** (0.11)			
Ln(1+UStar) × ImpGrowth	-0.002 (0.01)	-0.002 (0.01)	2.625*** (0.01)	-0.093 (0.07)	-0.010 (0.02)	-0.010 (0.02)	0.094 (0.07)			
Constant	2.126*** (0.00)	2.138*** (0.00)	2.625*** (0.01)	2.637*** (0.01)	-0.013*** (0.00)	-0.013*** (0.00)	-0.483*** (0.01)			
Adj. R ²	0.960	0.960	0.587	0.582	0.049	0.050	0.247			
N	7760896	7179683	6854311	6408393	7760896	7179683	6854311	6408393		

Note: The sample is the same as in Table 2. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(2) Customs regimes

China has a large share of processing trade under which foreign inputs can be imported duty-free for further processing, assembly, and reexporting. In our sample of Chinese exports to 131 non-US markets, processing export contributes about 30 percent during 2017-2019. Processing trade may react to US tariff shocks differently from ordinary trade, as it involves a foreign firm contracting with a Chinese factory manager to assemble intermediate inputs into a final product. Moreover, processing firms usually have very little control over the export prices and the destinations of their goods and are often the affiliates of foreign firms that directly control the transactions (Feenstra and Hanson, 2005). Thus, we separate the ordinary exports and processing exports and run the baseline regressions for the two sub-samples. As shown in Table B.4, we find the vertical trade diversion and quality upgrading continue to exist for ordinary trade, but the magnitudes of trade diversion and quality upgrading are smaller for processing exports.

Column (1) to (4) of Table B.4 use the sub-sample of ordinary trade, where the effects of US tariffs are similar to the total sample as reported in Table 2 and 4. More specifically, on an average destination market, we have an estimate of 0.341 for product-level trade diversion elasticity, 0.039 for export price elasticity and 0.524 for quality elasticity, while the quality-adjusted price elasticity is -0.424. These results indicate that Chinese firms under ordinary trade regime actively divert to third market destinations when facing tariff hikes in the US market, sell up-graded quality products and charge higher price, but the quality-adjusted price of their products decreases due to excess supply effect. Moreover, the patterns of trade diversion and quality upgrading are more pronounced in countries with lower income levels, smaller economies, and geographical proximity to China.

Column (5) to (8) of Table B.4 uses the sub-sample of processing trade. It was found that, while processing exporters also divert their products to third markets following the vertical trade diversion strategy, however, by a smaller magnitude of elasticity (0.198).

These firms also upgrade their exported product quality in low-income third markets but averagely speaking, the quality upgrading effect among all third markets no longer exists. Note that the price decreases (with elasticity of -0.121). One reasonable explanation is that the production activities of firms under processing trade regime are relatively more involved in the global value chains (GVC) of multi-national companies, and these firms have less degree of freedom in trade diversion strategy compared to their ordinary trade exporters counterpart.

Table B.4: Customs regimes

Sample by customs regimes Dependent Variable	Ordinary trade				Processing trade			
	Ln(exp) (1)	Ln(price) (2)	Ln(qap) (3)	Ln(quality) (4)	Ln(exp) (5)	Ln(price) (6)	Ln(qap) (7)	Ln(quality) (8)
Ln(1+UStar)	0.341*** (0.02)	0.039*** (0.01)	-0.424*** (0.05)	0.524*** (0.05)	0.198*** (0.04)	-0.121*** (0.03)	-0.023 (0.10)	-0.007 (0.10)
Ln(1+UStar) × GDPcapRatio	-1.358*** (0.09)	-0.362*** (0.05)	0.958*** (0.34)	-1.450*** (0.34)	-1.284*** (0.22)	-0.144 (0.13)	1.180** (0.57)	-1.589*** (0.59)
Ln(1+UStar) × GDPRatio	-5.815*** (0.69)	-0.429 (0.36)	8.947*** (2.42)	-10.343*** (2.47)	-9.953*** (1.25)	-1.792** (0.71)	7.489** (3.10)	-10.050*** (3.20)
Ln(1+UStar) × Ln(Dist)	-0.867*** (0.05)	0.012 (0.03)	2.898*** (0.16)	-2.891*** (0.17)	-1.396*** (0.11)	0.254*** (0.06)	3.437*** (0.27)	-3.299*** (0.28)
Ln(1+UStar) × ImpGrowth	0.016 (0.03)	-0.007 (0.02)	0.239** (0.09)	-0.245** (0.10)	0.059 (0.15)	0.347*** (0.09)	2.741*** (0.65)	-2.452*** (0.66)
Constant	10.355*** (0.00)	2.159*** (0.00)	2.073*** (0.01)	0.105*** (0.01)	10.769*** (0.01)	2.704*** (0.00)	0.762*** (0.02)	1.546*** (0.02)
Adj. R ²	0.512	0.815	0.232	0.092	0.496	0.843	0.467	0.379
N	6489124	6489124	6253338	6253338	1289470	1289470	1240511	1240511

Note: The full sample is the same as in Table 2, with a sub-sample of ordinary trade in Panel A and processing trade in Panel B. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(3) China's upstream tariff changes

During the trade war, China has adopted a "tit-for-tat" strategy in reaction to the US tariff war, imposing a wide coverage of reciprocal retaliatory tariffs on the US's products and leading to a sharp decline in the value and quantity of imports from the US (Ma et al., 2021). As argued by Fan et al. (2015), firms would adjust the quality and prices of exported products under tariff changes on imported inputs. Therefore, to further verify that the finding of vertical trade diversion is robust under China's retaliatory tariffs in upstream industries, we construct an upstream Chinese tariff exposure index ⁵ and include it into our baseline regressions. As shown in Table B.5 in Appendix (3), our findings on the patterns of vertical trade diversion, export prices, quality-adjusted prices, and quality upgrading are robust to the control of Chinese upstream tariff changes.

⁵See Appendix A.5 for its detailed definition.

Table B.5: Controlling for Chinese retaliatory tariffs in upstream imports

<i>Dependent Variable</i>	Ln(exp)	Ln(price)	Ln(qap)	Ln(quality)
	(1)	(2)	(3)	(4)
Ln(1+UStar)	0.355*** (0.02)	0.110*** (0.01)	-0.437*** (0.05)	0.549*** (0.05)
Ln(1+Up_CNtar)	-0.003*** (0.00)	-0.003*** (0.00)	0.003*** (0.00)	-0.006*** (0.00)
Ln(1+UStar) × GDPcapRatio	-1.279*** (0.09)	-0.522*** (0.05)	1.469*** (0.34)	-1.991*** (0.35)
Ln(1+UStar) × GDPRatio	-6.085*** (0.68)	-1.691*** (0.36)	9.400*** (2.46)	-11.071*** (2.51)
Ln(1+UStar) × Ln(Dist)	-0.991*** (0.05)	0.015 (0.03)	2.828*** (0.16)	-2.812*** (0.16)
Ln(1+UStar) × ImpGrowth	0.012 (0.03)	-0.010 (0.02)	0.195** (0.09)	-0.209** (0.09)
Constant	10.567*** (0.00)	2.147*** (0.00)	2.180*** (0.01)	0.009 (0.01)
Adj. R ²	0.532	0.822	0.214	0.081
N	7156397	7156397	6896993	6896993

Note: The sample includes all monthly export records with 131 non-US major trade partners to whom China's exports exceed \$500 million. The *Up_CNtar* is the tariff exposure from its upstream sectors' imports of US products facing China's retaliatory tariffs (see Appendix A.5 for its detailed definition). HS6-Month, Country-HS2 and Country-Time fixed effects are controlled. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(4) Full sample: all non-US trade partners

Table B.6: Trade diversion in all non-US trade partners

<i>Dependent Variable</i>	Ln(exp)	Ln(price)	Ln(qap)	Ln(quality)
	(1)	(2)	(3)	(4)
Ln(1+UStar)	0.336*** (0.02)	0.133*** (0.01)	-0.369*** (0.05)	0.507*** (0.05)
Ln(1+UStar) × GDPcapRatio	-1.294*** (0.09)	-0.499*** (0.05)	1.323*** (0.33)	-1.823*** (0.34)
Ln(1+UStar) × GDPRatio	-6.710*** (0.69)	-1.702*** (0.36)	10.475*** (2.45)	-12.146*** (2.50)
Ln(1+UStar) × Ln(Dist)	-0.904*** (0.05)	0.016 (0.03)	2.663*** (0.16)	-2.649*** (0.16)
Ln(1+UStar) × ImpGrowth	0.030 (0.02)	-0.022* (0.01)	0.123* (0.07)	-0.148** (0.07)
Constant	10.346*** (0.00)	2.132*** (0.00)	2.192*** (0.01)	-0.023*** (0.01)
Adj. R ²	0.540	0.815	0.213	0.083
N	7826927	7826927	7550468	7550468

Note: The sample includes all monthly export records with all non-US major trade partners. HS6-Month, Country-HS2 and Country-Time fixed effects are controlled. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(5) Comparison with Jiang et al. (2022)

Our finding that Chinese exporters divert more to the South based on all Chinese non-US trade partners may run counter to the result in Figure 6a in Jiang et al. (2022), where they find that China diverted more to the rich and large countries. The different conclusions stem largely from the methodological difference and the treatment of Chinese small trade partners. Here we briefly summarize their procedures. They first obtained the country-specific DID estimate of US tariff treatment on China's exports to each third market. Then they divide the countries into 20 bins and calculate the mean of countries' $\ln(\text{GDP per capita})$ and the mean of estimated coefficients for each bin, and they find a positive correlation between the mean of estimated coefficients and average destination income using the 20 data points (bins).⁶ This approach ignores the fact that China exports a very limited amount of goods to a large number of small trade partners. For example, Chinese total exports to the 108 small trade partners to which China exported less than 500 million USD in 2017 only account for about 0.6 percent of Chinese exports to non-US markets. Simply looking at the correlation between the bin-averaged country-specific DID estimates and destination country income level implicitly assumes equal weights for all Chinese non-US trade partners. This inflation of the weights of small trade partners may lead to biased conclusions.

A simple and transparent econometric approach is to include all Chinese non-US trade partners in one regression, and add the interaction terms of US tariff treatment dummies and destination country characteristics including $\ln(\text{GDP per capita})$, $\ln(\text{GDP})$, and distance to China.⁷ As shown in Table B.7, all three interactions are significantly negative, indicating that China diverted more to poorer, smaller, and closer markets, which ran against their conclusions drawn from the figure, but rather consistent with our findings.

⁶Note they use HS8 products while we use HS6 products, however, this pattern remains to hold using HS6 product level data. Thus, the aggregation of the data is not the driving force of differences between their findings and ours.

⁷This specification is similar to ours (Equation 2) except that we use the US tariff level rather than the US tariff treatment dummies.

Table B.7: Trade diversion in all non-US trade partners: DID estimates

<i>Dependent Variable</i>	Ln(exp)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}(\text{UStar}>0)$	0.577*** (0.03)	0.792*** (0.06)	1.314*** (0.07)	2.531*** (0.11)	2.529*** (0.11)	4.887*** (0.13)
$\mathbb{I}(\text{UStar}>0) \times \text{Ln}(\text{GDPcap})$	-0.058*** (0.00)			-0.050*** (0.00)	-0.050*** (0.00)	-0.146*** (0.00)
$\mathbb{I}(\text{UStar}>0) \times \text{Ln}(\text{GDP})$		-0.029*** (0.00)		-0.020*** (0.00)	-0.020*** (0.00)	-0.049*** (0.00)
$\mathbb{I}(\text{UStar}>0) \times \text{Ln}(\text{Dist})$			-0.142*** (0.01)	-0.169*** (0.01)	-0.169*** (0.01)	-0.256*** (0.01)
Constant	10.322*** (0.00)	10.320*** (0.00)	10.319*** (0.00)	10.345*** (0.00)	10.345*** (0.00)	10.342*** (0.00)
HS6-Month FE	+	+	+	+	+	+
Country-HS2 FE	+	+	+	+	+	
Country-Time FE	+	+	+	+	+	+
HS6-SprFes FE					+	+
Adj. R ²	0.540	0.539	0.538	0.539	0.539	0.481
N	8288728	8326665	8358648	8189613	8189523	8190117

Note: The sample includes all monthly export records with all non-US major trade partners. Robust standard errors clustered at country-product level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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