Essays on the Trade War, Processing Trade, and Global Value Chains

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Abstract

From 2018 to 2020, the trade war between the United States and China significantly raised trade barriers between the two largest economies in the world. My dissertation examines the economic consequences of the trade war, focusing on China's retaliation, and takes into account the presence of processing trade and global value chains. Whereas many recent studies have documented the effects of the trade war on the U.S. economy, less is known about the impacts on China. Notably, approximately 40% of Chinese imports are processing imports of intermediate inputs used in export-oriented products—which pay zero tariffs, even during the trade war.

In Chapter 1, I provide an overview of the trade war and its background, as well as a summary of efforts to assess its economic impacts. I discuss what we have learned to date from both the U.S. and China's perspective, focusing on three central topics: (i) tariff pass-through and trade elasticity, (ii) trade diversion and the role of global supply chains, and (iii) welfare impacts. I also emphasize the importance of considering processing trade and China's duty-free policy on processing imports empirically and quantitatively.

In Chapter 2, I conduct an empirical analysis of the impact of Chinese retaliation on China's import quantities and prices, highlighting the different effects on processing and non-processing trade. I do so by using monthly Chinese customs data from 2017 to 2019. I find significant reductions in non-processing imports from the U.S., whereas there is no significant effect on processing imports. This suggests that China's duty-free policy on processing trade may have served as a built-in mechanism to better protect domestic firms from damage by the trade war through the global value chain channel.

In Chapter 3, I build and calibrate a quantitative trade model that incorporates China's duty-free policy on processing imports to quantify the welfare and trade effects of the trade war. The model shows that the duty-free policy reduced China's welfare loss by 44%, and that China's imports and exports would have decreased significantly more if processing imports had not been exempted from the tariffs. These changes primarily affect industries in which processing trade is prevalent, and the model also shows considerable spillover effects on U.S. sectoral outcomes.

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Salute, cheers!

Nan Liu 刘南

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I dedicate this dissertation to my grandfather, Hongde Zhou. I miss you so much.

Contents

Chapter 1

The U.S.-China Trade War: An Overview

1.1 Introduction

After decades of trade liberalization and global market integration, the world witnessed an unprecedented trade war between the United States and China, its main trading partner, from 2018 to 2019. Chinese products were heavily targeted, with approximately \$350 billion of goods subjected to tariffs ranging from 10% to 50%. In retaliation, China imposed six rounds of tariffs on over \$100 billion of U.S. products and its average tariff reached the highest level since China joined the World Trade Organization in 2001. This substantial and unforeseen trade shock marks the most important trade policy shift in recent decades and offers a unique opportunity for researchers to examine the effects of trade protectionism.

I begin this chapter by outlining the background of the trade war. Next, I present a literature review in which I examine the diverse efforts to assess the economic impacts of the trade war. In particular, I review studies that have explored three central topics during the trade war: (i) tariff pass-through and trade elasticity, (ii) trade diversion and the role of global supply chains, and (iii) welfare impacts.[1] Lastly, I offer a detailed description of processing trade and China's duty-free policy on processing imports, and discuss the significance of considering processing trade in both empirical and quantitative studies.

First, a fundamental step in comprehending the impacts of the trade war is to investigate the pass-through of tariffs to import prices. This parameter is essential for estimating the distributional consequences of the trade war. Before the trade war, the literature typically found support for incomplete pass-through, which means that exporters would reduce pre-duty prices when tariffs increased. This finding forms the basis of tariff wars, since large importing countries can leverage terms of trade effects in their favor by implementing tariffs. However, contrary to expectations, recent studies have shown that neither U.S. nor Chinese exporters lowered their prices in response to the tariffs during the trade war. This implies that consumers in both countries have shouldered tariff burdens. In Section 1.3.1, I review the latest empirical papers that have investigated tariff incidence during the trade war.

Second, the detection of complete pass-through is directly linked to trade elasticities. For instance, one possibility is that the supply is highly elastic, and allows both the U.S. and China to effortlessly reallocate their exports to other destination countries. Empirical research has shown that trade war tariffs reduced imports and exports between the U.S. and China. However, total trade values for both countries

[1]This review is not intended to serve as a comprehensive survey. My perspective on the U.S.-China trade war, which may be considered idiosyncratic, omits numerous topics that others deem important. Instead, I will focus on discussing how the second and third chapters of this dissertation contribute to the related literature.

with the rest of the world have remained relatively stable or even increased. As a result, it is not surprising that global trade reallocation has taken center stage in the debate among economists. Confronted with higher tariffs, were importers seeking alternative sources from third countries? Were exporters redirecting products to the rest of the world? Furthermore, in the era of global value chains, if targeted products are less substitutable, the imposition of a tariff may be more significant because import tariffs can backfire on exporting. In Section 1.3.2, I review recent research that offers evidence on trade diversion effects and discuss the role of global supply chains during the trade war.

Lastly, who are the winners and losers of the trade war in terms of welfare effects? Given the estimated elasticities, it is straightforward to assess the magnitude of the welfare effects by performing simple back-of-the-envelope calculations. However, as the trade war unfolded, economists have employed various quantitative frameworks to examine the aggregate and distributional effects in general equilibrium across sectors and labor markets. Such quantitative trade models can measure the distinct mechanisms by which tariffs influence trade and welfare. In Section 1.3.3, I review recent efforts to quantify the impact of the trade war across different dimensions. I also discuss the latest data developments that can assist economists in performing trade policy counterfactuals.

Whereas many recent studies have documented the effects of the trade war on the U.S. economy, less is known about its impact on China; this may be due to data limitations. Investigating the consequences of China's perspective can enhance our understanding of the trade war's ramifications and the workings of global trade: Since 2009, China has been the world's largest exporter. It is also the second-largest importer and imports over $2,000 billion worth of products annually. Consequently, in each of the subsequent sections, I separately review papers that focus on either the U.S. or China's perspective.

While one might anticipate largely symmetrical results from the two countries' perspectives, they differ significantly in terms of trade structure and trade policy. In this chapter, I highlight a Chinese trade policy that has been overlooked in recent studies, which could result in biased estimates. Unlike the U.S., China is heavily engaged in processing trade, wherein domestic firms import intermediate inputs from foreign countries and re-export the final products after local processing and value addition. Approximately 40% of Chinese imports consist of processing imports of intermediate inputs used in export-oriented products. Most notably, all processing imports incur zero tariffs, and this policy remained unchanged even during the 2018-2019 trade war. In Section 1.4, I discuss this policy development in detail and clarify its role in analyzing trade-related topics within China's context, including the trade war.

1.2 Background

In recent decades, the United States has led efforts to reduce international trade barriers and foster global markets. Concurrently, China has experienced exponential growth in both imports and exports since its accession to the WTO and the attainment of permanent normal trade relations status in 2001. Nevertheless, the U.S. has treated China differently from other WTO members on multiple occasions through various trade policies. Prior to the Trump administration, both the Bush and Obama administrations implemented unilateral tariffs on Chinese products at different times. From 2018 to 2020, the Trump administration followed this precedent in pursuit of trade protection, but did so in an unprecedented manner. I provide a summary of the key events of the trade war; for more detailed information, please refer to Bown (2021) and Bown and Kolb (2023).

As a starting point, in February 2018, the Trump administration implemented safeguard tariffs on imports of washing machines and solar panels following a Section 201 investigation. These tariffs covered approximately $10 billion of U.S. imports. Shortly thereafter, Trump announced 25% tariffs on imports of steel and 10% on imports of aluminum. In response, China retaliated by implementing tariffs of 15%-25% on 128 products ($3 billion) of U.S. exports, including fruit and pork. At this stage, the magnitude of the trade war remained relatively small, and China was not the only targeted country; the European Union, Canada, Mexico, Argentina, Brazil, and South Korea all faced U.S. tariffs at varying levels. However, the trade war between the U.S. and China rapidly escalated, and soon overshadowed the initial waves of tariffs.

On July 6, 2018, Trump imposed 25% tariffs on $34 billion of imported products from China. In response, China also imposed 25% tariffs on $34 billion of U.S. imports, covering 545 products such as soybeans and cars. On August 23, the U.S. and China both implemented 25% tariffs on $16 billion of imports, bringing total trade coverage for tariffs to $50 billion.

From September 2018 onward, the trade war continued to escalate as the U.S. imposed 10% tariffs on an additional $200 billion of imports. The additional tariffs were further increased to 25% in June 2019. China retaliated by imposing 5%-10% tariffs on over 5,000 U.S. products with an annual trade value of approximately $60 billion. The retaliatory tariffs further increased to 5%-25% in June 2019. Notably, at this stage, it was no longer a "tit-for-tat" tariff war, since China could not match

U.S. tariffs in terms of the scope of targeted products and the magnitude of tariffs. This is because China's total imports from the U.S. accounted for only one-third of U.S. total imports from China.

In September 2019, Trump imposed additional 15% tariffs on $100 billion of Chinese products, followed by immediate retaliation from China. Another round of tariffs was scheduled to go into effect in December, but was ultimately canceled upon the Phase One agreement.[2] Nevertheless, the majority of products traded between the U.S. and China were subjected to trade war tariffs, and they remain in effect today.

In terms of scope and magnitude, by January 2020, 66% of Chinese exports were subject to U.S. tariffs, while 58% of U.S. exports were subject to Chinese tariffs. Average U.S. tariffs on Chinese products increased from 3.1% to 21%, while average Chinese tariffs on U.S. products rose from 8% to 21.8%. Of the targeted products, U.S. tariffs were heavily skewed toward intermediate inputs: 93% of imported intermediate inputs from China were covered, compared with 70% for final goods (Fajgelbaum et al. 2020; Handley et al. 2020; Bown 2021). Chinese retaliatory tariffs were more focused on agricultural, fishing, and auto industries, whereas key inputs such as semiconductors and aircraft parts were not subject to tariffs (Bown 2021).

It is worth highlighting the fact that both the U.S. and China exempted certain products from trade war tariffs, although the tariff exclusion processes were quite different. In December 2018, the United States Trade Representative (USTR) established a process by which American companies could submit temporary exclusion requests; some requests were accepted and others were denied.[3] Due to the lack of

[2]See Bown (2021) for a comprehensive discussion of the Phase One agreement. China eventually fell more than 40% short of fulfilling the purchase agreement in 2020 for various reasons, including the COVID-19 pandemic.

[3]Upon successful requests, importers may receive a rebate for the tariffs they have already paid.

full transparency in the exclusion process, it is challenging to determine who benefited. Also, filing the request may impose costs that small companies could not afford. Moreover, the factors the USTR considered in accepting or denying requests remain unknown. Nevertheless, the Trump administration announced more than 50 product exclusion lists and the Biden administration extended these products' tariff exemptions as they expired.[4] For example, the Apple Watch was exempted from 7.5% import tariffs, and some components of the Mac Pro were exempted from 25% tariffs. In 2020, all critical medical products were granted exclusion from U.S. tariffs due to COVID-19. However, all exclusions and rebates only affected about 4% of U.S. imports subject to trade war tariffs.

China also exempted certain products during the trade war. Most notably, China exempted all processing imports from tariffs.[5] For example, of the $60 billion U.S. products targeted in the June 2019 wave, 34.8% were processing imports that paid zero tariffs. This suggests that overlooking China's duty-free policy on processing imports could lead to miscalculations of trade coverage or trade-weighted average tariffs.

Beyond tariffs, non-tariff instruments were also used during the trade war. For instance, in 2019, the U.S. placed Huawei and SMIC on the Entity List, which prohibited U.S. products and services from being sold without an export license. Limits were also imposed on exporting semiconductors to Chinese companies. China's non-tariff barriers for U.S. agricultural and manufacturing exports also increased significantly, with a focus on a small number of products such as soybeans (Chen et al. 2022).

[4]Products on the exclusion lists were at the level of a product description, which is a more disaggregated level than HS-10 codes. Therefore, it is extremely difficult to match the exempted products to =trade data (Bown 2021)

[5]See Section 1.4 for a detailed discussion of this policy.

However, measuring such non-tariff instruments is challenging, and more systematic analyses are needed. In the following sections, I will concentrate on the literature that examines the effects and implications of trade war tariffs.

1.3 Literature Review

1.3.1 Tariff Pass-through and Trade Elasticity

Recent literature has offered new perspectives on the effects of the U.S.-China trade war. Among the various empirical studies, a central question concerns tariff pass-through. A standard regression analysis investigates how pre-duty prices responded to trade war tariffs:

$$\Delta log[p^*_{ict}] = \eta \Delta log(1 + \tau_{ict}) + FEs + \epsilon_{ict}. \tag{1}$$

Typically, p^*_{ict} represents before-duty price measured as a unit value at HS-8 or HS-10 level. τ_{ict} denotes the statutory tariffs of product i from country c at time t. Different studies incorporate various fixed effects, since the sources of variation differ.

Amiti et al. (2019); Amiti et al. (2020); and Fajgelbaum et al. (2020) estimated this equation using monthly U.S. customs data. They found no impact of U.S. tariffs on pre-duty prices—i.e., the prices received by Chinese exporters. The finding of complete pass-through suggests that U.S. tariffs have been entirely passed through to domestic prices. This is surprising for a large economy like the U.S., since conventional wisdom is that such economies can leverage terms of trade effects in their favor by implementing tariffs.

Several hypotheses might explain the finding of complete pass-through. First, complete pass-through could reflect inelastic demand or elastic supply. Fajgelbaum et al. (2020) estimate a U.S. demand system combined with foreign export supply curves. Their results suggest an infinitely elastic foreign export supply, but with a finite and relatively low demand elasticity across origin countries. These results differ from previous estimated elasticities. Fajgelbaum and Khandelwal (2021) use the estimated import demand and export supply elasticities of Romalis (2007); Broda and Weinstein (2006); and Soderbery (2015) and find that all of these estimates support incomplete pass-through. Second, it is possible that during the trade war, both U.S. and Chinese import tariffs on intermediate inputs increased costs for Chinese manufacturers through the global supply chain. Consequently, Chinese exporters adjusted to this cost shock by raising their prices, which may mask an upward-sloping supply curve. However, examining this hypothesis requires detailed data on the import-export linkages within firms.

Whereas most recent studies have focused on the results for the U.S., understanding the outcomes from China's perspective can help us better comprehend the consequences of the trade war and the mechanics of global trade. Using monthly customs data in China, Jiang et al. (2023) investigate how Chinese exports respond to the U.S. tariffs. They find a decrease in Chinese export quantities, with prices remaining relatively unchanged. They also estimate the average trade elasticity and find smaller values than those inferred from the import data in the U.S. by Fajgelbaum et al. (2020). Therefore, it is worth discussing the differences between the estimates using U.S. import data and Chinese export data.

First, discrepancies in trade data due to different data collection processes have long been documented in the literature (Feenstra et al. 1999; Jiang et al. 2023). Second, the identification strategies differ. For instance, Fajgelbaum et al. (2020) implement equation (1) and control for product-time, exporter-time, and exporter-sector fixed effects in their benchmark specification. Therefore, the identification stems from differential variation in monthly tariff changes across exporters to the U.S. within a product. That is, they compare the differences between imports from China and imports from other countries, between products that were subject to different tariffs, and before and after the date of tariff implementation (triple difference). However, because Jiang et al. (2023) use Chinese export data, their identification is based only on the comparison of targeted and untargeted products by Chinese exporters to the U.S. before and after the date of tariff implementations (difference-in-differences).

Another strand of the literature explores the response of Chinese importers facing Chinese retaliatory tariffs. Chang et al. (2021); Ma et al. (2021); and Tian et al. (2022) implement specifications similar to those in Amiti et al. (2019) and Fajgelbaum et al. (2020), but from China's perspective, and find complete pass-through. In the subsequent chapter, using monthly import data from the Chinese customs, I also find supporting evidence for the complete pass-through of Chinese tariffs. More importantly, I highlight the differing effects on processing and non-processing imports. In contrast to the U.S., China is deeply involved in processing trade, in which domestic firms import intermediate inputs from foreign countries, process them locally, and re-export the final products after adding value. Approximately 40% of Chinese imports are processing imports of intermediate inputs used in export-oriented products. Most notably, all processing imports pay zero tariffs, and this policy remained unchanged even during the trade war.

In Chapter 2, I demonstrate that while Chinese non-processing import quantities decreased sharply following the Chinese retaliatory tariffs, there were no significant effects on processing imports. Therefore, it is crucial that we exclude processing imports from the sample when studying the response of Chinese importers.[6] Similarly, researchers must consider this policy when studying the response of U.S. exporters. For instance, Amiti et al. (2019) estimate the effects of retaliatory tariffs on U.S. exporters by comparing targeted U.S. goods with the same U.S. goods exported to other destinations. However, in the U.S. export data it is impossible to distinguish whether a U.S. export transaction was classified as a processing import in China. Therefore, using the Chinese government's announced retaliatory tariff rate as τ_{ict} in equation 1 could be problematic.

Finally, recent studies have estimated the tariff pass-through and trade elasticities at different levels of aggregation. Due to data restrictions, earlier research could only access country-product-level customs data—i.e., there was no firm-level information. More detailed data were only available for specific sectors or cities. Cavallo et al. (2021) estimate tariff pass-through using BLS micro-data.[7] They find relative price reductions in U.S. products targeted by China. They also collect millions of online prices from two large multichannel retailers and find that consumer prices were barely affected by trade war tariffs. Using retail price data on washing machines, Flaaen et al. (2020) document complete pass-through of U.S. tariffs to consumer prices. Using data that covers all firms that export to foreign countries in a Chinese prefecture-level city, Jiao et al. (2022) find that U.S. tariffs did not affect the free-on-board price of Chinese exports after controlling for firm-related fixed effects. They also surveyed 600 Chinese firms and found evidence that 21% of firms faced impediments to adjusting prices due to contractual agreements.

Recently available universal firm-level customs data from the U.S. and China pro-

[6]The Chinese customs data record each transaction's trade regime, which allows researchers to distinguish processing trade from non-processing trade.

[7]The BLS collects U.S. import price data by survey to construct import price indices.

vide new insights into tariff pass-through. Using confidential data from the U.S. Census, He et al. (2023) find that the pass-through on U.S. importers is incomplete at disaggregated firm-product-country level. They also find that firm heterogeneity, which is absent in the country-product level data, is the main driver for the incomplete pass-through. However, using disaggregated firm-product-level data from Chinese customs, Tian et al. (2022) find complete pass-through of Chinese retaliatory tariffs. Therefore, depending on the level of aggregation and the identification strategy, the evidence on complete pass-through seems somewhat mixed. Nevertheless, the availability of more detailed data provides researchers with a great opportunity to study the effects of trade protectionism from different perspectives. For example, firm-level customs data can reveal essential information on trade diversion as well as import-export linkage within firms, which I will discuss in the next subsection.

1.3.2 Trade Reallocations and Global Supply Chains

Recent empirical studies have documented significant decreases in bilateral trade quantities between the U.S. and China following trade war tariffs (Amiti et al. 2019; Fajgelbaum et al. 2020; Ma et al. 2021). In Chapter 2, I also show that a 1% increase in Chinese retaliatory tariffs leads to a 0.82% decrease in Chinese import quantities. However, while the estimated trade reductions between the U.S. and China have the expected correlations, there is less evidence on trade reallocations from the U.S./China to the rest of the world. More specifically, how did the U.S.-China trade war affect global trade? Did importers/exporters seek alternative source/destination countries? Did other countries take over the market share of U.S./Chinese products?

Fajgelbaum et al. (2023) develop a framework to estimate countries' export responses to third-country tariffs. For each country, they consider the change in product-level exports to the U.S., China, and the rest of the world as a function of the U.S.-China tariffs. They find that on average, third countries increased their exports to the U.S., barely changed their exports to China, and increased their exports to the rest of the world. Theses results suggest that the trade war created net trade opportunities for countries other than the U.S. and China. On the import side, Nicita (2019) and Berthou and Stumpner (2020) calculate the change in imports from third countries and show that the total decrease in U.S. imports from China was compensated for by an increase in imports from other countries. However, Berthou and Stumpner (2020) find remarkably different patterns for China: The reduction in Chinese imports from the U.S. was not countered by more imports from third countries, but rather was reinforced by a fall in imports from third countries. In Chapter 2, by examining the relationship between Chinese import tariffs and Chinese imports from the rest of the world, I also do not find a significant import trade diversion effect for China, and there is no evidence that third countries were taking over the share of U.S. products in Chinese imports. On the export side, Jiao et al. (2022) find that Chinese firms' exports to the U.S. dropped significantly, exports to the E.U. increased moderately, and exports to third countries were barely affected by U.S. tariffs. Jiang et al. (2023) also find that U.S. tariffs have little effect on Chinese total exports to the world as a whole.

Estimating trade reallocation effects systematically is particularly challenging, due to the complexity of modern global value chains. For instance, the reallocation of a specific country-product pair may impact other country-product pairs along these value chains. I now shift the focus to discuss the role of global value chains during the trade war.

Compared with the global economy during passage of the Smoot-Hawley Tariff Act in the 1930s, countries are now deeply interconnected through global value chains.[8] Recent studies suggest that the trade war could be more costly and divisive in this era of global value chains, because import tariffs might backfire on domestic production (Blanchard 2019; Boehm et al. 2019). Within the context of the trade war, Handley et al. (2020) show that a significant share of U.S. exports faced increased tariffs on imported intermediate inputs during the trade war, which led to an even larger decline in exports. Flaaen and Pierce (2019) find that the protection received by U.S. manufacturing industries more exposed to tariff increases was offset by the negative effects of rising input costs. Tian et al. (2022) find that Chinese retaliatory tariffs imposed on upstream firms led to a greater decline in firms' final exports. Zhou (2022) shows that U.S. tariffs on imports of Chinese upstream intermediate goods negatively affected U.S. downstream exports, output, and employment.

These results emphasize the importance of considering trade in intermediate inputs and sectoral linkages when studying the impact of the trade war. Notably, U.S. trade war tariffs were heavily skewed toward intermediate inputs, such as primary metals and electrical equipment (Fajgelbaum et al. 2020; Handley et al. 2020). In contrast, China's duty-free policy on processing imports acted as a built-in mechanism that exempted a significant share of intermediate inputs from its retaliatory tariffs. In Chapter 3, I incorporate this duty-free policy into a multi-country, multi-sector model to quantify the welfare impact of the trade war. The model demonstrates that the policy reduced China's welfare loss by approximately half. It also reveals that

[8] Please refer to Antras and Davin (2022) for a survey of the importance of global value chains in shaping international trade flows and multinational activity.

not only would China's imports have decreased significantly more but so would its exports if processing imports had not been exempted from the tariffs. These findings ultimately contribute to discussion of the target of unilateral import tariffs.[9] One of the primary objectives of the trade war was to protect certain industries and bring jobs back to the U.S. However, this came at a cost, since global value chains are pervasive in most protected sectors, and the increase in producer costs is detrimental to the competitiveness of U.S. producers (Bellora and Fontagné 2019).

1.3.3 Aggregate and Distributional Welfare Effects

Recent literature has employed general equilibrium models to quantify the aggregate and distributional effects of the trade war. Fajgelbaum et al. (2020) measure the welfare changes resulting from the trade war by calculating the aggregate equivalent variation (EV), or the change in aggregate real income. Their method offers several appealing properties. First, it is applicable in neoclassical environments regardless of the input-output structure. Second, it has minimal data requirements: Pre-war trade flows and tariffs, as well as post-war price and quantity changes, are sufficient (Fajgelbaum and Khandelwal 2021). They find that the losses to U.S. importers and consumers amounted to 0.27% of GDP. After accounting for tariff revenue and gains to U.S. producers, the aggregate real income loss for the U.S. was 0.04% of GDP. This finding is consistent with the observation of incomplete pass-through, since U.S. consumers bore most of the tariff burden. They further examine the distributional impacts of the trade war across regions and reveal that U.S. import tariffs favored sectors concentrated in politically competitive counties, while retaliatory tariffs had

[9] See Caliendo and Parro (2021) for a comprehensive discussion of optimal trade policy in a neoclassical environment and in models with monopolistically competitive heterogeneous firms.

the most negative effect on the tradable sector in predominantly Republican counties.

Another strand of the literature employs Ricardian models of trade with a gravity structure to quantify the various mechanisms through which the trade war affected trade and welfare. These frameworks build on Eaton and Kortum (2002). The models can capture the interactions across countries and sectors observed in input-output tables, which allows researchers to decompose and quantify the differential roles of intermediate goods and sectoral linkages as amplifiers of losses from the trade war. Researchers can also use these models to perform various trade policy counterfactuals. Caliendo and Parro (2021) estimate the welfare effects of the trade war in a multi-sector framework with input-output linkages. They find that the trade war resulted in a decline in real wages in the United States of about 0.13% and in China of about 0.11%. When taking into account tariff revenues, they find that real income slightly declined in both countries. Moreover, both countries would have been better off if China had not retaliated. By introducing a spatial framework to the model, they also find highly heterogeneous real wage losses across different states. In Chapter 3, I extend the model from those of Caliendo and Parro (2015) and Caliendo and Parro (2021) to incorporate China's duty-free policy on processing imports. I find that real wages in China decreased by 0.09% and real income decreased by 0.1%. In the counterfactual exercise, I find that if China had not exempted processing imports from tariffs, it would have suffered a real wage loss of 0.13% and a real income loss of 0.18%. I also find that this policy has a heterogeneous sectoral impact, and the significant changes in aggregate welfare effects are primarily driven by industries in which processing trade is prevalent.

Several other papers examine the welfare effect of the trade war using various quantitative frameworks. Zhou (2022) builds a two-stage, multi-country, multi-sector general equilibrium model based on Antras and Davin (2020) and finds that the trade war cost China 0.29% of GDP and the US 0.08% of GDP. Grossman et al. (2023) construct a model that features firm-to-firm supply relationships, in which firms engage in costly searches for potential input suppliers to form global supply chains in anticipation of free trade. Then, with the unexpected trade war tariffs, firms renegotiate prices or search for replacements. Their model suggests a welfare loss of 0.5% of GDP for the U.S. Overall, estimated aggregate welfare losses appear to be small across different quantitative trade models.

I conclude this section by discussing several datasets that have been widely used in trade war-related quantitative work. Part of the progress in quantitative trade policy analysis in recent years has resulted from the availability of publicly accessible cross-country, cross-sector input-output tables, or world input-output tables (WIOTs). Various institutions have produced different WIOTs, such as the Global Trade Analysis Project (GTAP), the Eora Global Supply Chain Database (Eora), the OECD Inter-Country Input-Output Tables (OECD ICIO), and the World Input-Output Database (WIOD). While they have distinct features, all of these datasets aim to harmonize and merge domestic input-output tables provided by member countries; these are supported by more disaggregated data, e.g., national supply and usage tables (SUTs).

However, one significant caveat of these SUTs is that they do not distinguish imported inputs across source countries at the level of individual industries and final demand categories. As a result, most WIOTs' data construction relies on the "proportionality assumption" that imports are distributed proportionally among individual industries and final consumers. Recent improvements have been made to construct different proportionality weights using the BEC classification, along with detailed product-level trade data. Nevertheless, the proportionality assumption can still be problematic; for example, U.S. shares of textiles purchased by China's textile industry would be identical to those purchased by China's auto industry (Antras and Davin 2022). This issue becomes more challenging in the trade war context, since a large share of Chinese imports are processing imports that are only used in several industries as intermediate inputs.

Fortunately, the latest version of the OECD Inter-Country Input-Output Tables (OECD ICIO) addresses the heterogeneity of production in China by dividing its IO tables into two distinct structures, which provides me with the essential data to calibrate the model in Chapter 3. Specifically, the OECD ICIO uses an extended Chinese input-output table that accounts for the dual trade regimes in China. This extended IO framework was developed by a research team from the Chinese Academy of Sciences and the National Bureau of Statistics, using microdata such as manufacturing firm surveys and customs data.[10]

In addition to WIOTs, the development of tariff databases has also facilitated quantitative trade policy analysis. For instance, the World Integrated Trade Solution (WITS) offers bilateral tariffs at HS-6 level for the majority of countries worldwide. These detailed tariff lines are extremely useful for calculating trade-weighted average tariffs for various manufacturing sectors in different WIOTs. However, in the context of China, it is crucial that we use only non-processing imports as weights, since processing imports are duty-free. For example, in Chapter 3, I demonstrate that the changes in trade-weighted Chinese retaliatory tariffs differ when using only non-processing imports as weights compared with using all imports as weights.

[10] See Chen et al. (2019) and Chen et al. (2020) for a detailed discussion of distinguishing China's processing trade in the WIOTs.

1.4 Processing Trade

Processing trade is a unique trade regime in which domestic firms import intermediate inputs and capital equipment from foreign countries, process them locally to add value, and then export the finished products. To encourage exports, a key feature of processing trade is the exemption from tariffs (or the provision of rebates) on imported intermediate goods and capital equipment, provided that they are used exclusively to produce goods intended for export. This duty-free policy is typically implemented by establishing export processing zones or issuing special licenses. Processing trade is particularly common in developing countries with relatively low labor costs, such as China, Mexico, and Vietnam, and has played a crucial role in the economic development of those economies (Brandt et al. 2021).

Processing trade in China began to flourish in 1979, following the country's reform and opening up. The share of processing imports then experienced rapid growth, increasing from around 10% in the early 1980s to approximately 63% in 1997 (Yu 2015). After China joined the WTO in 2001, the share of processing imports gradually decreased, but still constitutes around 40% of total imports. The share of processing exports also rose swiftly between 1990 and 2000 to over 50% before experiencing a slight decline in the 2000s (Brandt and Morrow 2016; Kee and Tang 2016). Contrary to expectations, in 2000, only 42% of Chinese processing exports were consumer goods such as electronics and textiles, while 32% were intermediate inputs and 25% were capital equipment (Brandt et al. 2021). Table 1.1 provides simple summary statistics for Chinese imports during the trade war. Overall, at HS-8 product level, non-processing imports account for approximately 60% of the total import value, while processing imports make up about 40%.

Table 1.1: Chinese Imports by Trade Regimes

Imports by Trade Regimes	2017	2018	2019
Percentage of total import value			
Non-processing imports	58.7	59.7	60.5
Processing imports	39.3	39.1	38.0

Among all types of processing trade, two are the most significant: "Processing-with-assembly" and "Processing-with-inputs."[11] "Processing-with-assembly" involves Chinese firms that imports raw materials or parts from their foreign partners without paying for materials or customs duties. After processing and adding value, the final products must be re-exported to the same foreign partners. This trade regime was more prevalent before the 1990s, since it imposed fewer credit constraints on Chinese processing firms. However, it now only accounts for a small portion of Chinese imports. In the "Processing-with-input" regime, domestic Chinese firms initially pay for raw materials and customs duties for imported inputs. After local processing, Chinese firms can sell the final goods to any foreign country. They will then receive a full rebate on import duties after exporting goods that used these imported inputs.[12]

Three types of Chinese firms participate in importing/exporting activities. First, non-processing (ordinary) firms can purchase/sell goods from/to domestic markets or foreign countries. However, they cannot participate in processing trade and do not enjoy the duty-free policy. In contrast, pure processing firms can import intermediate inputs from foreign countries and purchase domestic inputs with zero tariffs, but they cannot sell their final products to the domestic market. The third type of firm is the

[11] Other types of processing trade include foreign aid, compensation trade, goods on consignment, goods on lease, border trade, contracting projects, outward processing, barter trade, customs warehouse trade, and entrepôt trade by bonded area.

[12] If a Chinese firm imports foreign inputs but sells the final products to the domestic market after processing, customs duties will not be refunded.

Table 1.2: Chinese Imports from the United States by Firm Type

	Firms	Products (HS-8)	Value (mil USD)
Ordinary	25,961 (47.6%)	4,725	3,393 (22.7%)
Pure Processing	6,074 (11.1%)	3,416	2,691 (18.0%)
Hybrid Processing	22,525 (41.3%)	5,581	8,864 (59.3%)
Ordinary Imports		*5,238*	*5,599*
Processing Imports		*4,415*	*3,264*
Total	54,560	5,983	14,947

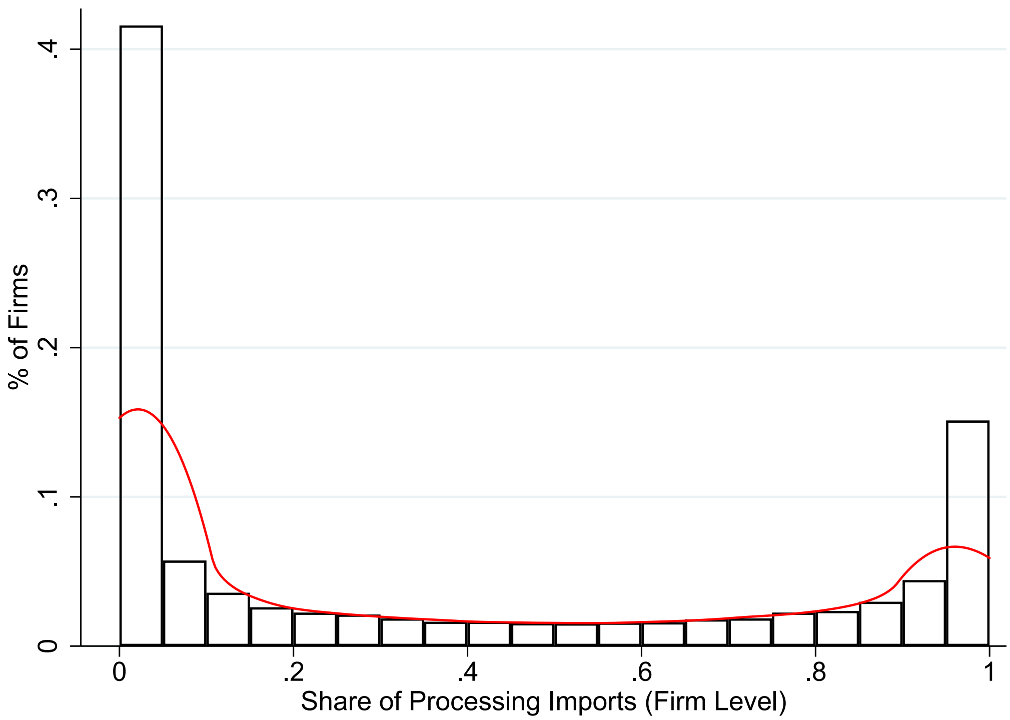
hybrid firm, which can engage in both non-processing trade and processing trade. They enjoy the duty-free policy on their processing imports but must pay the tariffs for their non-processing imports.[13]

Table 1.2 reports Chinese imports from the United States by firm type using 2015 firm-level Chinese customs data. As shown, approximately 48% of Chinese firms importing from the U.S were non-processing (ordinary) importers, 11% were pure processing importers, and the remaining 41% were hybrid importers. In total, processing imports accounted for 40% of Chinese imports from the U.S. in 2015. Notably, most hybrid firms concentrated on one type of trade. Figure 1.1 demonstrates that the share of processing imports was less than 5% in over 40% of hybrid firms participating in processing trade with the U.S., even though they were eligible for processing trade. In contrast, 15% of hybrid importers engaged in pure processing imports, with a share of processing imports greater than 95%.

Firms that participate in processing trade in China are required to obtain specific certifications and licenses from the Department of Foreign Trade and Economic Cooperation in each province. First, they need licenses for importing/exporting, and then

[13]Meanwhile, foreign-invested enterprises (FIEs) play an important role in processing trade. In the early 2000s, FIEs accounted for over 60% of China's processing exports (Feenstra and Hanson 2005). In 2018, FIEs handled nearly 80% of processing trade (Tian et al. 2022).

Figure 1.1: Share of Processing Imports within Hybrid Importers



Note: Figure 1.1 displays the distribution of Chinese hybrid importers involved in processing trade with the U.S. at various levels. The vertical axis shows the percentage of Chinese hybrid importers, and the horizontal axis represents the share of processing imports at firm level. Each bin has a width of 0.05, and the values are calculated using the 2015 Chinese customs data.

they need to provide contracts with foreign partners as proof to obtain the licenses for processing trade. To prevent tax evasion, the Chinese government and customs impose strict regulations on firms engaged in processing trade. Firms are required to document and report the storage, resale, transportation, loss, and usage of all raw materials and parts. In some provinces, hybrid firms must store raw materials and parts used in processing trade separately from non-processing trade. Failure to comply with these regulations may result in high penalties.

Under certain circumstances, if a Chinese firm imports foreign inputs but sells the final products in the domestic market after processing, customs duties will not be refunded. However, this type of transaction is relatively small. It is worth noting that different countries have different policies on selling processing outputs in the domestic market. For example, Mexico now allows processing firms to sell up to 90% of their products in the domestic market.

The importance of China's duty-free policy on processing imports has been widely recognized in the literature, with numerous studies highlighting its role in the country's economic development (e.g., Feenstra and Hanson 2005; Yu 2015; Brandt and Morrow 2016; Kee and Tang 2016; Brandt et al. 2021; Tian and Yu 2019; Yu and Zhu 2019). However, recent literature on the trade war has paid relatively little attention to this policy. It is crucial that we consider this policy in any analysis of the trade war, for several reasons. First, although the Chinese government claimed to implement retaliatory tariffs in the same magnitude as the U.S. tariffs, in practice significantly fewer Chinese imports were subject to tariff increases. Failing to account for this policy could lead to biased welfare estimates. Second, the policy played an important role in mitigating the impact of the trade war on Chinese processing firms. Without it, these firms would have faced export impediments and more expensive intermediate inputs during the trade war. Finally, the policy has spillover effects on the U.S. economy, since it affects the production of goods that rely on Chinese processing imports. For example, if China imposed tariffs on screen glass made by Corning in Kentucky, the retail price of an iPhone in the U.S. could be higher, depending on the tariff pass-through rate. In the next two chapters, I will evaluate the economic consequences of the trade war in the presence of processing trade and assess the role of China's duty-free policy on processing imports.

1.5 Conclusion

The U.S.-China trade war is a significant event that presents a unique opportunity for researchers to study the effects of trade protectionism. In this chapter, I provide background information on the trade war, including its timing, scale, and the scope of products subject to tariff changes. I also discuss products that were excluded from tariffs and non-tariff barriers and review and summarize efforts to assess the economic impacts of the trade war. I focus on three main topics: (i) tariff pass-through and trade elasticity, (ii) trade diversion and the role of global supply chains, and (iii) welfare impacts. For each topic, I discuss what we have learned to date from the perspective of both the U.S. and China and highlight how my dissertation contributes to the literature. Throughout this chapter, I emphasize the role of processing trade and China's duty-free policy on processing imports. I provide a detailed description of the institutional details and discuss the importance of considering processing trade both empirically and quantitatively works. Overall, this chapter aims to provide a comprehensive overview of the U.S.-China trade war and its impacts on the global economy.

Chapter 2

Trade War from the Chinese Trenches

2.1 Introduction

After decades of trade liberalization and global market integration, the world has witnessed the break out of an unprecedented trade war between the United States and its trading partners starting from 2018. Such a large and unexpected trade shock marks the most important trade policy shift in recent decades, which provides an unusual opportunity for researchers to study the effects of trade protectionism. However, whereas most recent studies have documented the effects of this trade war on the U.S. economy, less is known about the impacts on China.

Examining the effects from China's perspective can help us better understand the consequences of the trade war and the mechanics of global trade. China has been the largest exporter in the world since 2009. It is also the second largest importer and imports over $2,000 billion worth of products annually, with the U.S. as one of the most important source countries. Moreover, in contrast to the U.S., China is deeply involved in *processing trade*, in which domestic firms import intermediate inputs from foreign countries and re-export the final products after processing locally and adding value. Approximately 40% of Chinese imports are processing imports of intermediate inputs used in export-oriented products. Most notably, all processing imports pay zero tariffs, and this policy remained unchanged even during the 2018-2019 trade war.

In this chapter, I use monthly Chinese customs data from 2017 to 2019 to estimate the effects of Chinese retaliation on China's import quantities and prices, and highlight the different effects on processing and non-processing trade. Additionally, I investigate the possibility of trade diversion (substitution) effects to assess whether Chinese importers are searching for alternate source countries to import goods from.

The reduced-form estimates reveal significant declines in Chinese imports when China implemented retaliatory tariffs. I find that a 1% increase in Chinese retaliatory tariffs leads to a 0.82% decrease in import quantities and a 1.17% decrease in the import values of targeted products. Prices of imports targeted by Chinese tariffs only slightly fell, implying marginal pass-through. However, the reductions are entirely from non-processing imports; there is no significant effect on processing imports, which were exempt from the import tariffs. These findings are also consistent with the results revealed by an event-study framework.

By examining the relationship between Chinese import tariffs and Chinese imports from the rest of the world other than the U.S., I do not find a significant import trade diversion effect. There is also no evidence showing that third countries were taking over the share of U.S. products in Chinese imports. The results are consistent across products that vary in terms of differentiation or elasticity of substitution.

A key challenge in getting unbiased estimates in this chapter is to address the potential endogeneity of tariff changes. The estimation requires the trade war tariffs to be exogenous and uncorrelated with potential supply and demand shocks. Most rounds of tariffs from both China and U.S. were announced and enacted in a very short time-period. Therefore, anticipation effects may not have enough time to play an important role. I also perform several robustness checks by testing pre-trends, and by visualizing the trends before and after the tariffs were being implemented using an event-study framework. The results show that there is no significant pre-trend before the tariffs were implemented.

The subsequent sections of this chapter are organized as follows. Section 2.2 provides a detailed description of the data used in the analysis. Section 2.3 outlines the main empirical specifications and presents the estimation outcomes. Finally, Section 2.4 provides concluding remarks.

2.2 Data

In this chapter, the primary data used for the reduced-form estimation is the administrative monthly Chinese customs data, covering the period from January 2017 to December 2019. This dataset records the universe of Chinese import and export transactions, providing various information for each transaction such as product (HS-8 level), quantity, and value. More importantly, this dataset also records the trade regime for each transaction, which allows me to analyze the effects on processing and non-processing trade separately.

Since the custom duties or tariff lines are not directly observable in the customs data, I use a combination of data from various sources to construct a monthly panel data of tariffs. The Ministry of Finance of China provides the trade war tariffs data,

Table 2.1: Summary Statistics: Chinese Retaliatory Tariffs

Date	# of Products	Value	Rates	Processing Imports
Apr 2, 2018	128	2.97	15%; 25%	24.9%
July 6, 2018	545	33.83	25%	12.7%
Aug 23, 2018	333	14.11	25%	20.5%
Sep 24, 2018	5207	58.16	5%; 10%	31.8%
June 1, 2019	4544	40.22	5%; 10%; 15%	34.8%
Sep 1, 2019	1717	28.66	5%; 10%	17.8%

Notes: Table 2.1 presents an overview of the six waves of Chinese import tariffs, reported at HS-8 level. The value of each wave, measured in billion USD, is computed as the 2017 annual Chinese import value of targeted products. The share of processing imports is computed as the value of processing imports over the 2017 annual Chinese import value of targeted products in each wave.

which are primarily set at HS-8 level and expressed as ad valorem tariffs. Since multiple rounds of tariffs were enacted in the middle of the month, I adjust the tariffs by scaling them according to the number of days they were in effect.[1]

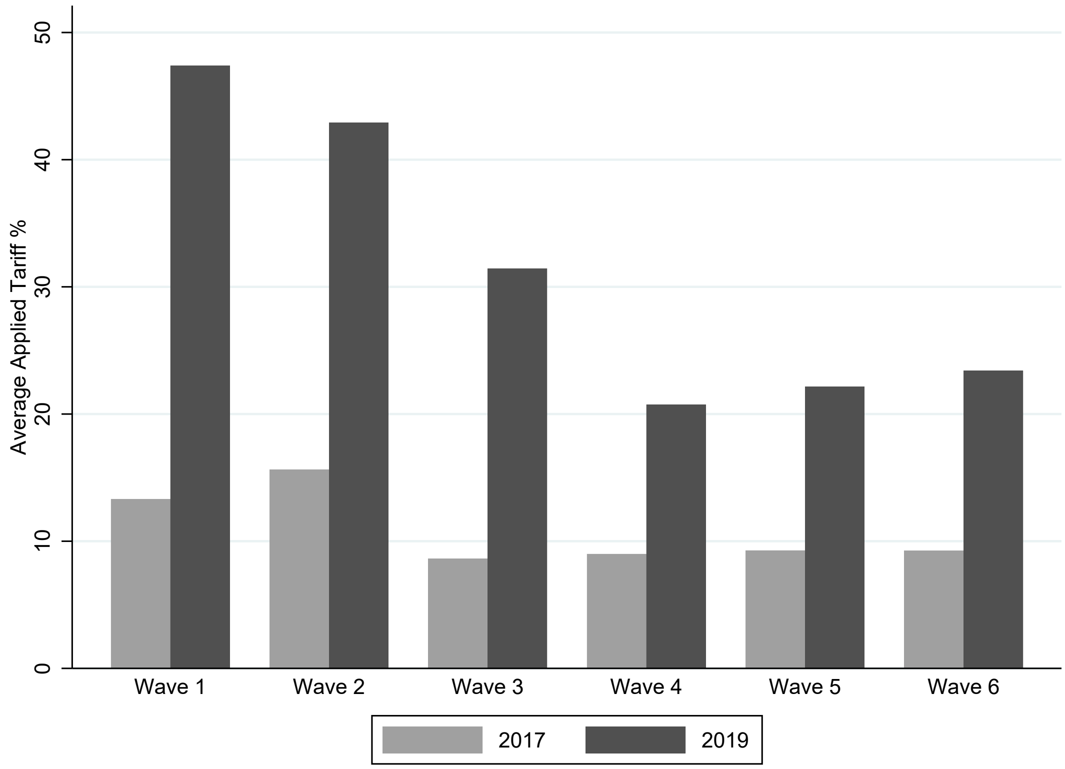
To establish the baseline Chinese import tariffs, I initially gather the Most Favored Nation (MFN) tariff rates at HS-8 level published by the central government of China one year before the commencement of the trade war. Next, I compile a list of country-product pairs that are subjected to regional trade agreements, such as the tariffs applied to products from the Association of Southeast Asian Nations (ASEAN), from 35 least-developed countries (LDC), and from other countries or regions that have entered into specific trade agreements with China.[2] Lastly, I calculate the effective Chinese import tariff rate for each country-product pair by adding the baseline tariff rate and the announced trade war tariffs.

Table 2.1 presents an overview of the Chinese import tariffs during the trade

[1]For instance, if a 25% tariff was enacted on June 15, then the effective tariff will be $25 \times 15/30 = 12.5\%$ in June and 25% in the following month.

[2]These encompass South Korea, Laos, Macao, New Zealand, Pakistan, Peru, Singapore, Sri Lanka, Switzerland, Taiwan, Chile, Australia, Iceland, Costa Rica, Georgia, and Hong Kong.

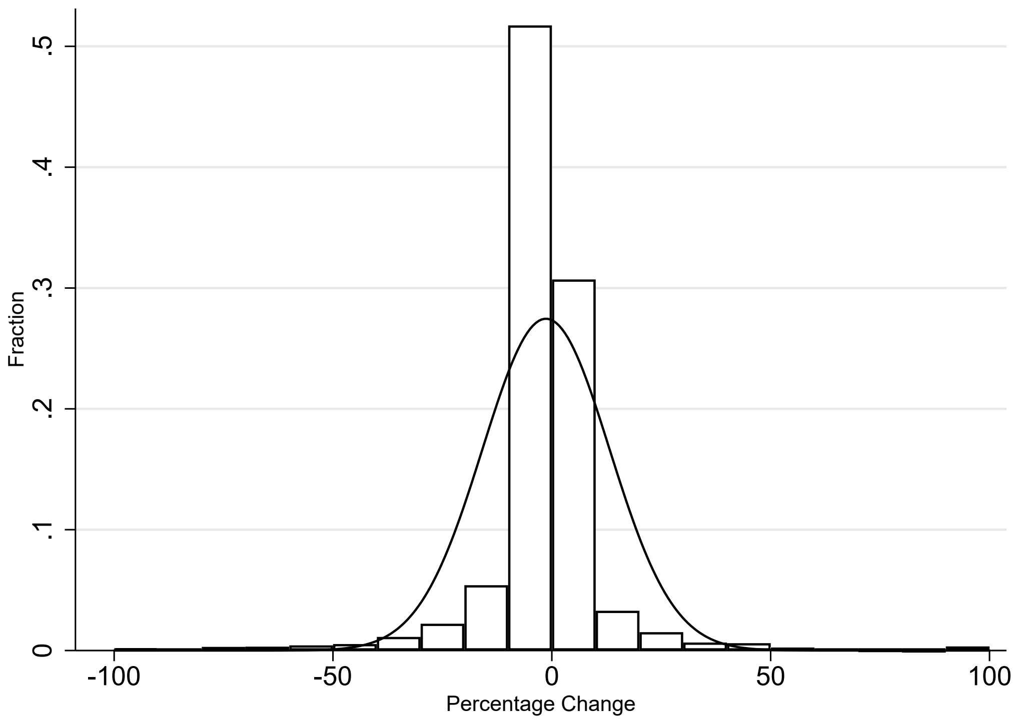
Figure 2.1: Average Chinese Import Tariffs



Notes: Figure 2.1 shows the unweighted average applied Chinese import tariff rates for products targeted in each tariff wave. The light grey bar shows the tariffs in 2017 (pre-trade war), and the dark grey bar shows the tariffs in 2019.

war. In response to the U.S. tariffs on steel and aluminum, China's initial wave of retaliatory tariffs in April 2018 targeted 128 HS-8 level products from the U.S. A second wave in July 2018 targeted 545 distinct products, primarily agricultural, with a total value exceeding $30 billion. Additional tariffs were added in September 2018, which expanded to most products imported from the U.S. and were later increased in scale. It is worth noting that some product lists were revised during the trade war, and some products were targeted multiple times. Finally, a significant share of targeted products were processing imports, which are exempt from paying any tariffs. The last column of Table 2.1 shows the share of processing imports exempted from

Figure 2.2: Change in the Quantity Share of U.S. Product in Chinese Imports



Notes: Figure 2.2 shows the changes in the quantity share of U.S. products in Chinese imports. The horizontal axis displays the percentage change in the share of each U.S. product at HS-8 level from 2017 to 2019, with a bin width of ten percentage points. The vertical axis represents the fraction of U.S. products in each bin. The curve reflects the scaled normal density.

the tariffs in each wave.

Figure 2.1 presents the changes in unweighted average tariffs on products targeted in each of the six waves. For the products targeted in the first three waves, the average ad valorem tariff increased to over 30%. In the later stage of the trade war, most products imported from the U.S. were subjected to over 20% tariffs.[3]

To demonstrate the effect of the trade war on Chinese imports by isolating price

[3]Multiple tariff increases occurred for many products from 2017 to 2019, resulting in an overall increase in applied tariffs for products targeted in each tariff wave that could be higher than the announced tariff rates of each wave.

effects, Figure 2.2 shows the changes in the quantity share of U.S. products in Chinese imports from 2017 to 2019. The analysis is conducted by calculating the percentage change in the quantity share of each U.S. product at HS-8 level, followed by grouping them into ten percentage points bins. The vertical axis presents the proportion of U.S. products that fall into each bin, while the curve displays the scaled normal distribution. Results indicate that a substantial proportion of U.S. products experienced declines in quantity share of Chinese imports from 2017 to 2019. Nonetheless, for more than half of U.S. products, the reductions are relatively small, ranging from 0% to 10%. Over 30% of U.S. products even observed an increase in their quantity shares, implying a mixed effect of the trade war on the import of U.S. products by China.

2.3 Empirical Strategy and Estimation

2.3.1 Event-study Framework

To better visualize the dynamic effects of tariff increases on Chinese imports, this section presents an event-study framework. Specifically, I compare the trends of targeted products from the U.S. with the same HS-8 products from other countries which were not subject to the tariff increases. The equation I estimate is as follows:

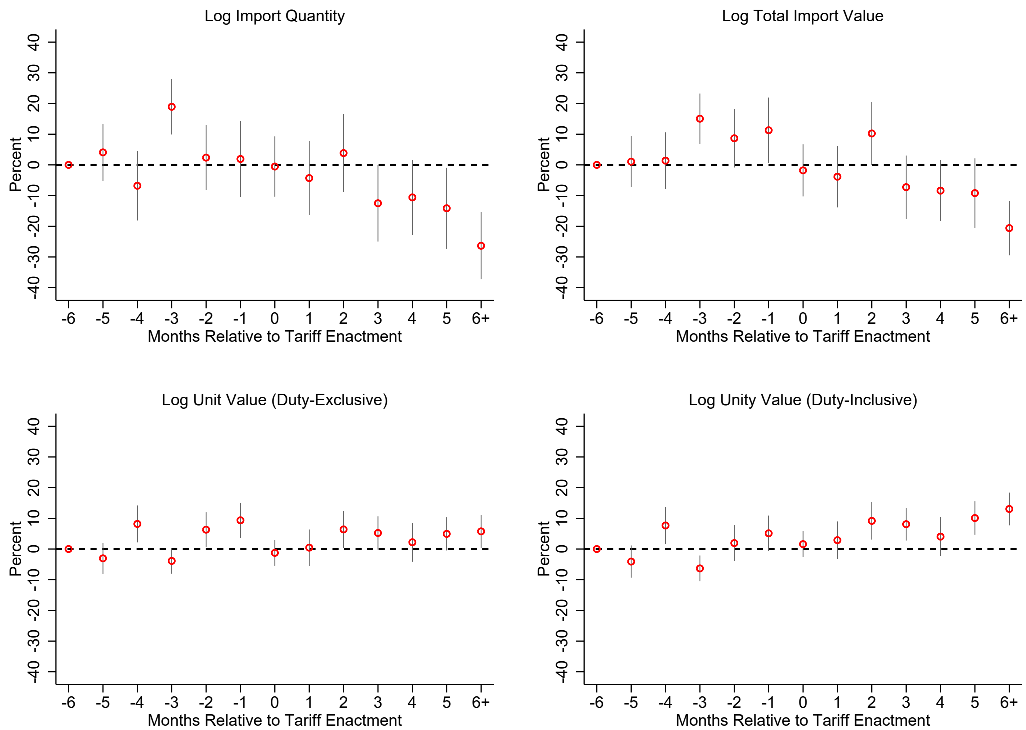
$$log[y_{ict}] = \sum_{j=-6}^{j=6} \beta_{0j} \mathbb{1}[t=j] + \sum_{j=-6}^{j=6} \beta_{1j} \mathbb{1}[t=j] \times Target_{ic} + f_{ic} + f_{ct} + f_{it} + \epsilon_{ict},$$

where y_{ict} represents quantity, value, duty-exclusive unit value or duty-inclusive unit value for product i (HS-8) from country c at month t. j represents the introduction time of each round of tariffs. $Target_{ic}$ equals to one if product i from country c was subject to the Chinese retaliatory tariffs and equals to zero otherwise. I include product-country fixed effects f_{ic} as the identification is coming from time variation by variety (country-product pair). f_{it} is the product-month fixed effects controlling for demand variation and seasonality. f_{ct} is month-country fixed effects controlling for time-varying country factors such as exchange rates. The standard errors are clustered at HS8-country level. β_{1j} is the coefficient of interest. It is identified using variation between targeted variety (those directly affected by a tariff increase) to the non-targeted variety within the same HS product code at the same time. Following Fajgelbaum et al. (2020), the event date of targeted product is the nearest full month when the tariffs were enacted. Non-targeted varieties in the same HS code as a targeted variety are assigned the earliest event date (tariff wave) within that HS code.[4] Event times less than -6 (i.e., 6 months before the roll out) are dropped and event times greater than 6 are binned together. Therefore, this event study framework only shows the trend in the very short run.

In Figure 2.3, the top two panels depict the effects of Chinese retaliation on import quantities and values, respectively, while the bottom panels illustrate the effects on before-duty and after-duty unit values. The error bar represents the 95% confidence interval of the estimates. Although the estimates are not very precise, they suggest downward trends in import quantities and values after the implementation of tariffs. The before-duty unit values display fluctuations, but they are mostly insignificant. In contrast, the duty-inclusive unit values increased by approximately 10% following the tariffs.

[4]For example, if a product from the U.S. was first targeted in the Sep 24 wave, the event date for this product from other countries (non-targeted) will be October 2018.

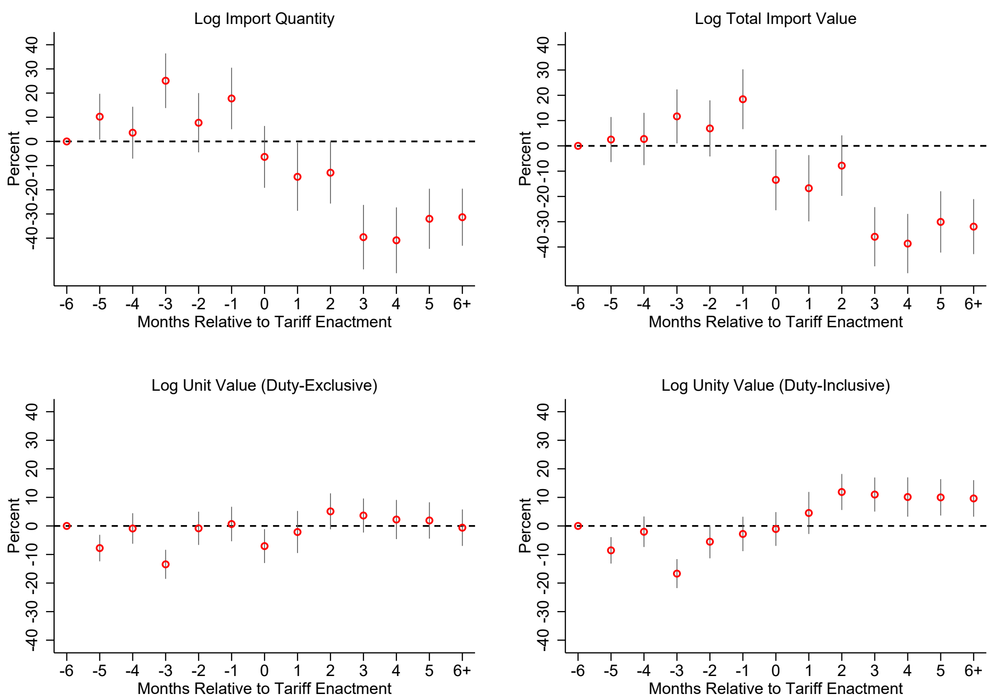
Figure 2.3: Event-study: All Imports



Notes: Figure 2.3 plots the estimated event-study dummies for targeted varieties relative to untargeted varieties. Regressions include country-product, product-time, and country-time fixed effects. Standard error are clustered at country-HS8 level. Event time before -6 are dropped, and event time $\geqq 6$ are binned. The sample period is 2017:1 to 2019:12. Error bar shows 95% confidence interval.

During the trade war, China's duty-free policy on processing imports remained unchanged, which implies that non-processing imports should subject to a more significant impact compared to processing imports, at least in the short run. To test this hypothesis, I conducted the event-study analysis separately on China's processing and non-processing imports using the trade regime information available in the customs data. As shown in Figure 2.4, China's non-processing (ordinary) imports experienced a significant decline in quantities and values after the implementation of retaliatory tariffs. The before-duty unit values were not significantly different from zero, while

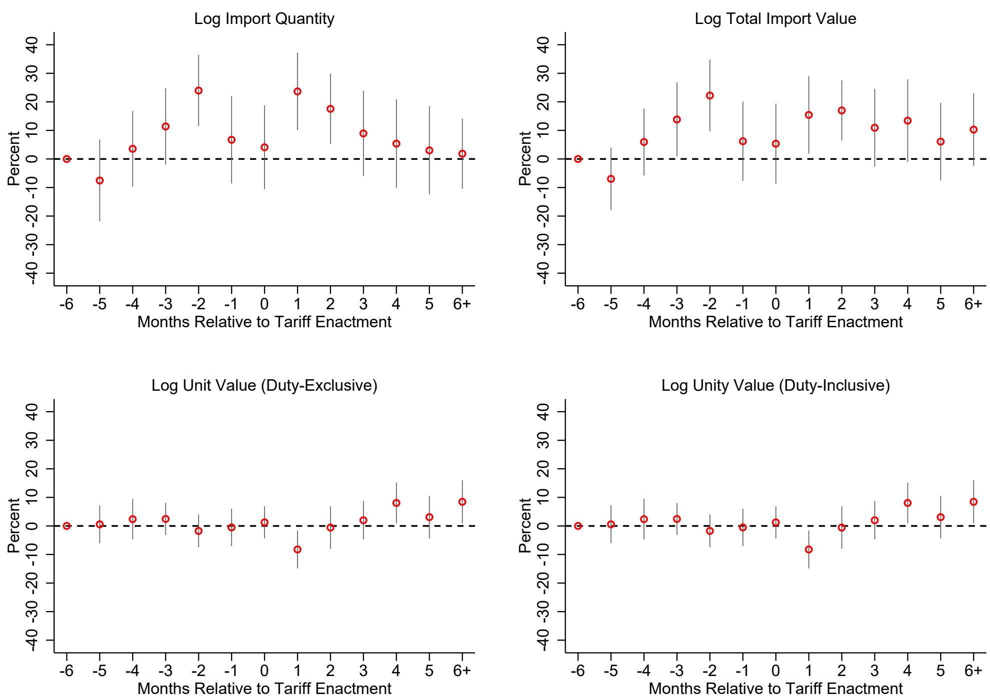
Figure 2.4: Event-study: Non-processing Imports



Notes: Figure 2.4 plots the estimated event-study dummies for targeted varieties relative to untargeted varieties. Regressions include country-product, product-time, and country-time fixed effects. Standard error are clustered at country-HS8 level. Event time before -6 are dropped, and event time $\geqq 6$ are binned. The sample period is 2017:1 to 2019:12 and only non-processing imports are included. Error bar shows 95% confidence interval.

the duty-inclusive unit values increased by around 10% following the tariffs. On the other hand, Figure 2.5 shows that the quantities and values of processing imports increased slightly following China's retaliatory tariffs, with no significant change in unit value for processing imports. The findings suggest that the trade war may lead to more firms engaging in processing trade to avoid extra import duties. The implications of the reallocation in trade modes due to the trade war tariffs are worth further investigation.

Figure 2.5: Event-study: Processing Imports



Notes: Figure 2.5 plots the estimated event-study dummies for targeted varieties relative to untargeted varieties. Regressions include country-product, product-time, and country-time fixed effects. Standard error are clustered at country-HS8 level. Event time before -6 are dropped, and event time $\geqq$ 6 are binned. The sample period is 2017:1 to 2019:12 and only processing imports are included. Error bar shows 95% confidence interval.

2.3.2 Impact of Chinese Tariffs on Chinese Imports

This subsection provides reduced-form evidence on how Chinese import prices and quantities move in response to the retaliatory tariffs. The equation I estimated is as follows:

$$\Delta log[z_{ict}] = \eta \Delta log(1 + \tau_{ict}) + f_{ct} + f_{it} + f_{ic} + \epsilon_{ict},$$

where $z \in \{q,\ p{\times}q,\ p^*,\ p\}\equiv$ {import quantity, import value, duty-exclusive unit value, duty-inclusive unit value}. τ_{ict} represents the statutory import tariff rates ,and Δ represents the month-to-month differences. All changes in retaliatory tariffs, China's MFN tariffs, and RTA are considered. The regression includes country-time fixed effects, product-time fixed effects, and product-country fixed effects to control for seasonality, time-varying country-specific factors (such as exchange rates), and product-country time-invariant trends. Under the assumption that the import tariffs enacted by the Chinese government are exogenous, the coefficient of interest η is identified using variation in product-country-level over time. The robust standard errors are clustered by country and HS-8.

Table 2.2 Panel A reports the responses of Chinese imports to the tariff changes, pooling processing and non-processing (ordinary) imports. It shows import quantities did not change significantly, whereas import values decreased in response to the retaliatory tariffs. Table 2.2 Panel B shows the estimates using non-processing (ordinary) imports only. Column (1) shows that import quantities decreased by 0.82% following the tariff increases. Column (2) shows that a 1% increase in tariffs lead to a 1.17% decrease in Chinese import values. Column (3) shows that a 1% increase in tariffs resulted in a 0.35% decrease in duty-exclusive unit values, although the estimate is not very precise. Column (4) shows that a 1% increase in tariff resulted in a 0.65% increase in duty-inclusive unit values.[5] In contrast, Panel C shows that there is no significant change in quantities and prices of Chinese processing imports in response to the retaliatory tariffs.

A key challenge in obtaining unbiased reduced-form estimates is to address the potential endogeneity of tariff changes. This requires that the trade war tariffs be

[5]Because I do not directly observe the duty-inclusive unit value in the data, I impute the duty-inclusive unit value as $p = p^* \times (1 + \tau)$. Therefore mechanically, the coefficient in column (4) is one plus the coefficient in column (3).

Table 2.2: Impact of Chinese Tariffs on Chinese Imports

Panel A: All Imports				
	$\Delta ln q_{ict}$ (1)	$\Delta ln p^*_{ict} q_{ict}$ (2)	$\Delta ln p^*_{ict}$ (3)	$\Delta ln p_{ict}$ (4)
$\Delta ln(1+\tau_{ict})$	-0.33	-0.69**	-0.36**	0.64***
	(0.34)	(0.33)	(0.15)	(0.15)
Product × time FE	Y	Y	Y	Y
Country × time FE	Y	Y	Y	Y
Product × country FE	Y	Y	Y	Y
R^2	0.13	0.14	0.11	0.11
N	2,307,350	2,307,350	2,307,350	2,307,350
Panel B: Ordinary Imports				
	$\Delta ln q_{ict}$ (1)	$\Delta ln p^*_{ict} q_{ict}$ (2)	$\Delta ln p^*_{ict}$ (3)	$\Delta ln p_{ict}$ (4)
$\Delta ln(1+\tau_{ict})$	-0.82**	-1.17***	-0.35*	0.65***
	(0.36)	(0.39)	(0.20)	(0.20)
Product × time FE	Y	Y	Y	Y
Country × time FE	Y	Y	Y	Y
Product × country FE	Y	Y	Y	Y
R^2	0.14	0.15	0.12	0.12
N	1,954,678	1,954,678	1,954,678	1,954,678
Panel C: Processing Imports				
	$\Delta ln q_{ict}$ (1)	$\Delta ln p^*_{ict} q_{ict}$ (2)	$\Delta ln p^*_{ict}$ (3)	$\Delta ln p_{ict}$ (4)
$\Delta ln(1+\tau_{ict})$	-0.28	-0.32	-0.04	0.96***
	(0.33)	(0.31)	(0.18)	(0.18)
Product × time FE	Y	Y	Y	Y
Country × time FE	Y	Y	Y	Y
Product × country FE	Y	Y	Y	Y
R^2	0.16	0.17	0.13	0.13
N	1,092,999	1,092,999	1,092,999	1,092,999

Notes: Table 2.2 presents the estimated responses of import quantities, values, before-duty unit values, and duty-inclusive unit values at the variety-level to changes in Chinese import tariffs. Columns (1)-(4) report the regression results using changes in statutory tariff rates (including MFN and RTA changes during the trade war) as the main explanatory variable. The sample is divided into three panels: Panel A includes all import transactions, Panel B includes only ordinary imports, and Panel C includes only processing imports. All regressions use month-to-month differences and control for product-time, country-time, and product-country fixed effects. Robust standard errors clustered by country and HS-8 are reported in parentheses. Significance levels are indicated by * for 0.10, ** for 0.05, and *** for 0.01. The sample period is from January 2017 to December 2019.

exogenous and uncorrelated with potential supply and demand shocks. Since most rounds of tariffs from both China and the U.S. were announced and enacted in a short period, anticipation effects may not have had enough time to play a significant role. Additionally, I performed a test, and Table A1 in the Appendix shows that there were no significant preexisting trends.

2.3.3 Import Trade Diversion

To formally assess the extent of trade diversion (substitution), I propose a simple regression to examine the relationship between Chinese import tariffs and Chinese imports from the rest of the world, excluding the U.S. This would help study whether Chinese importers were substituting across source countries during the trade war, potentially leading to a reorganization of global value chains. The equation I estimate is as follows:

$$\Delta log(RoW_i) = \beta \Delta log(1 + Tariff_i^{CHN}) + f_i + \epsilon_i,$$

where on the left hand side, I take the difference of the total Chinese import quantities (and values) of product i at HS-6 level from all countries other than the U.S. between 2019 Q4 and 2017 Q4. Because many products experienced multiple rounds of tariff increases, comparing the change before (2017 Q4) and after (2019 Q4) the trade war yields a less noisy trend. On the right hand side, $Tariff_i^{CHN}$ represents the trade weighted effective Chinese trade war tariffs on product i at HS-6 level.[6] f_i represents the product fixed effects at HS-2 level and the robust standard error ϵ_i is clustered at

[6] I examine the impact at HS-6 level because HS codes across countries are not comparable at HS-8 level.

Table 2.3: Import Trade Diversion Effect

	Δlog(RoW Quantity) (1)	Δlog(RoW Value) (2)
$\Delta log(1 + Tariff_i^{CHN})$	-0.44*	-0.29
	(0.24)	(0.19)
Product FE (HS-2)	Y	Y
R^2	0.05	0.06
N	4,711	4,711

Notes: Column (1)-(2) report total import quantities and values from all third countries other than the U.S. regressed on trade weighted Chinese retaliatory tariffs at HS-6 level. The changes are from 2017 Q4 to 2019 Q4. Both regressions include product fixed effects at the HS-2 level. Robust standard errors in the parentheses are clustered at HS-6. Significance: * 0.10, ** 0.05, *** 0.01.

HS-6 level.

Table 2.3 shows that overall there is little evidence that the Chinese import tariffs have impact on Chinese import quantities and values from the rest of the world. This result is consistent with Berthou and Stumpner (2020) in which they find the reduction in Chinese imports from the U.S. are not countered by more imports from third countries but reinforced by a fall in imports from third countries.

To further assess the trade diversion effect at product-level, I choose a subset of products in which the U.S. had a share greater than 20 percent in Chinese imports before the trade war in 2017, containing 902 products at HS-6 level. Next, for products where the U.S. was the largest source country in 2017, I calculate the share of the second largest source country, and for products where the U.S. was not the largest source country, I calculate the share of the largest source country. By comparing the changes in these third countries' shares from 2017 to 2019, I find that the average difference was 0.01 with a standard deviation of 0.17. This further implies that despite the Chinese import tariffs on U.S. products, third countries were not taking over the US share in Chinese imports.

One possible explanation for the lack of significant trade diversion effects found in the previous analysis is the potential heterogeneity across products or sectors. For example, Cavallo et al. (2021) find that some U.S. exporters reduced their prices in response to Chinese retaliatory tariffs, particularly for agricultural and non-differentiated goods. This may eliminate the need for Chinese importers to seek alternative sources. To explore this potential source of heterogeneity, I interact the Chinese import tariffs with the Rauch classification (Rauch 1999) and import demand elasticities estimated by Soderbery (2015) in Table A2 in the Appendix. However, neither interaction term yields significant results. This suggests that although there may be heterogeneity across different product characteristics, there is no significant effect of these characteristics on trade diversion.

2.4 Conclusion

This chapter examines the effects of the trade war between the U.S. and China from China's perspective. Using monthly Chinese customs data from 2017 to 2019, I estimate the effects of Chinese retaliation on China's import quantities and prices, and highlight the different impacts on processing and non-processing trade. The findings reveal significant declines in Chinese imports following the implementation of retaliatory tariffs, and there is only marginal pass-through to pre-tax import prices. The reductions are entirely from non-processing imports, with no significant effect on processing imports, which were exempt from import tariffs. Moreover, there is no significant import trade diversion effect or evidence that third countries were taking over the share of U.S. products in Chinese imports.

A key challenge in obtaining unbiased estimates is addressing the potential endogeneity of tariff changes. However, the results of several robustness checks indicate that the trade war tariffs were exogenous and uncorrelated with potential supply and demand shocks.

The findings of this chapter provide insight into the consequences of the trade war on China and highlight the importance of considering China's duty-free policy when estimating the impact of the trade war. Motivated by these results, in the next chapter, I use a quantitative general equilibrium model with sectoral linkages, trade in intermediates goods, and sectoral heterogeneity in production to quantify the welfare and trade effects of the trade war, taking processing trade into consideration.

Chapter 3

Trade War, Processing Trade, and Global Value Chains

3.1 Introduction

In Chapter 2, I estimated the effects of Chinese retaliatory tariffs on Chinese import quantities and prices, highlighting the different effects on processing and non-processing imports. Motivated by the reduced-form estimates, I build a workhorse quantitative model of international trade that accounts for sectoral linkages through traded intermediate inputs to gauge the welfare impact and perform policy experiments in this chapter. A key feature of the model is that it incorporates China's duty-free policy on processing imports. In the counterfactual exercises, I show how the economic consequences would change if China had not exempted processing imports from tariffs.

The model is based on Caliendo and Parro (2015). It captures the interactions across countries and sectors observed in an input-output table so that I can decompose and quantify the differential roles of intermediate goods and sectoral linkages as amplifiers of losses from the trade war. However, incorporating China's duty-free policy on processing imports in the model faces several difficulties. For example, a Chinese firm that engages in processing production could have fundamentally different productivity compared with a firm that does non-processing production, even if they are producing the same good. Therefore, I model China as two economies: One engages only in processing production, and the other only in non-processing production. By doing so, I consider China to be two trade regimes that share a single labor market and aggregate demand, which is a realistic characterization of the institutional setup in a Ricardian quantitative trade model. Calibrating the extended model requires detailed data on trade flow and input-output linkages across countries and sectors that distinguish China's processing production from non-processing production. Most widely used input-output data, such as the World Input-Output Database (WIOD), do not consider such heterogeneity. Fortunately, the latest OECD inter-country input-output (ICIO) database addresses this issue by providing a separate IO table for China's processing and non-processing production, which provides me with the data needed to calibrate the extended model.

I find that the duty-free policy on processing imports significantly reduces China's welfare loss from the trade war. Under the duty-free policy, real wages in China decreased by 0.09%. Once the changes in tariff revenues are taken into account, real income in China decreased by 0.1%. In contrast, if China did not exempt processing imports from tariffs, it would have suffered a real wage loss of 0.13% and a real income loss of 0.18%. I also find that this policy has a heterogeneous sectoral impact, and the significant changes in aggregate welfare effects are primarily driven by industries in which processing trade is prevalent. For example, without the policy, the largest processing industry in China (Computer) represents 18% of the decline in real income, whereas it was only 7% when processing imports were exempt from tariffs. For the United States, I find that the trade war resulted in a decline in real wages of about 0.15%. However, once the changes in tariff revenues are taken into account, I find a slight increase in real income of about 0.03%. I also find considerable sectoral spillover effects from China's duty-free policy: U.S. industries that are deeply connected to China via processing trade contribute more to the U.S. gain in real income.

The model also predicts significantly smaller trade effects for China when considering processing trade. I find that China's imports would have decreased by 9.34% and exports would have decreased by 6.99% due to the trade war if processing imports had not been exempted from tariffs. In contrast, China's imports only decreased by 4.36% and exports only decreased by 3.49% under the duty-free policy. The differences primarily come from Computer, Electrical, and Textile industries, in which processing production is prevalent. Notably, the duty-free policy not only led to smaller reductions in Chinese imports but also prevented import tariffs from backfiring on Chinese exports. The model also predicts that U.S. imports would have decreased by 5.4% and export by 9.92%. However, I do not find any significantly different trade effects for the United States when considering China's duty-free policy on processing imports.

Building on Caliendo and Parro (2015, 2021), this paper incorporates China's duty-free policy on processing trade in a multi-country, multi-sector model. Previous studies do not distinguish China's processing trade from non-processing trade in a framework with sectoral input-output linkages. This may lead to bias, because traditional input-output tables mix imports that are not directly relevant to tariff increases. By using the latest inter-county input-output table from the OECD, I can separately estimate the parameters and assign the correct sectoral tariffs to China's processing and non-processing production, which yields welfare estimates that reflect the actual policy.

Intuitively, China's duty-free policy serves as a built-in mechanism that exempts a significant share of intermediate inputs from its retaliatory tariffs. While the trade war reduced overall welfare, the results from this chapter suggest that China's duty-free policy on processing imports at least reduced its welfare cost.

The remainder of this chapter is structured as follows. Section 3.2 provides a detailed description of the model, while Section 3.3 outlines the data and calibration methodology. The results and counterfactual exercises are presented in Section 3.4, and Section 3.5 concludes.

3.2 A Quantitative General Equilibrium Model

This section presents a quantitative general equilibrium model with trade in intermediate goods, sectoral heterogeneity, and input-output linkages. I extend the framework from Caliendo and Parro (2015) to incorporate China's duty-free policy on processing imports.

3.2.1 The Model

Consider a world economy with N countries that are indexed by i and n. In each country i, there are J sectors that are indexed by j and k. In order to incorporate China's processing production into the model, I treat China as two economies: One doing non-processing (ordinary) production and trade only, the other doing processing production and trade only. For convenience, denote $CN1$ China's ordinary production, denote $CN2$ China's processing production, and denote CN the aggregate of $CN1$ and $CN2$. The relationship between these two economies will be discussed in detail below.

In each country, there are a measure of L_n representative households that maximize utility by consuming final goods C_n^j and the utility functions are given by

$$u(C_n) = \prod_{j=1}^{J} C_n^{j\,\alpha_n^j}, \text{where} \sum_{j=1}^{J} \alpha_n^j = 1. \tag{1}$$

Denote by I_n household income. I_n derived from two sources: household supply labor L_n at a wage w_n and receive transfers on a lump-sum basis. Labour is mobile across sectors. Moreover, labor is freely mobile between $CN1$ and $CN2$, and the wages are the same as $CN1$ and $CN2$ share the same labor market. To be specific, $I_{CN} = I_{CN1} + I_{CN2}$, $L_{CN} = L_{CN1} + L_{CN2}$ and $w_{CN} = w_{CN1} = w_{CN2}$. By doing so, I consider China as two "trade regimes" that share a single labor market and aggregate demand, which is a realistic characterization of the institutional setup in China.

A continuum of intermediate goods $\omega_j \in [0, 1]$ is produced in each sector j. Two types of inputs, labor, and composite intermediate goods (materials) from all sectors, are used for the production of each ω_j. Producers of intermediate goods across countries differ in the efficiency of production. Denote the efficiency of producing intermediate good ω_j in country n by $z_n^j(\omega_j)$. The production technology of a good ω_j is

$$q_n^j(\omega_j) = z_n^j(\omega_j)[l_n^j(\omega_j)]^{\gamma_n^j} \prod_{k=1}^{J} [m_n^{k,j}(\omega_j)]^{\gamma_n^{k,j}},$$

where $l_n^j(\omega_j)$ is labour, $m_n^{k,j}(\omega_j)$ is the composite intermediate goods from sector k used for production of intermediate good ω_j, and the parameter $\gamma_n^{k,j} \geq 1$ is the share of materials from sector k used in the production of intermediate good ω_j. $\sum_{k=1}^{J} \gamma_n^{k,j} = 1-\gamma_n^j$, where $\gamma_n^j \geq 0$ is the share of value added. Notice that the production technology for $CN1$ could differ from that for $CN2$. In reality, processing firms in China could potentially have different technologies than non-processing firms. For example, Tian et al. (2022) points out that from 2018 to 2019, foreign-invested enterprises (FIEs) handled nearly 80% of processing trade, and FIEs may have different technologies than domestic Chinese firms.

Assume production of intermediate goods is constant return to scale and markets are perfectly competitive. Firms price at unit cost, and $c_n^j / z_n^j(\omega_j)$. c_n^j is the cost of an input bundle, and

$$c_n^j = \Phi_n^j w_n^{\gamma_n^j} \prod_{k=1}^{J} P_n^{k\,\gamma_n^{k,j}}, \tag{2}$$

where P_n^k is the price of a composite intermediate good from sector k, and Φ_n^j is a constant. $CN1$ and $CN2$ have the same w_n, but have different γ_n^j, P_n^k, and $\gamma_n^{k,j}$.

Producers of composite intermediate goods in sector j country n supplies Q_n^j at minimum cost by purchasing intermediate goods ω^j from the lowest cost suppliers across countries[1]

$$Q_n^j = \left[\int r_n^j(\omega^j)^{1-1/\sigma^j} d\omega^j \right]^{\sigma^j/(\sigma^j-1)},$$

where $\sigma^j > 0$ is the elasticity of substitution across intermediate goods within sector j, the demand of intermediate goods ω^j from the lowest cost supplier is then given

[1] Specific types of processing firms, especially those who do "processing-with-assembly", are not searching lowest cost suppliers across countries. Instead, they sign contracts with foreign partners and import raw intermediate inputs before processing and exporting them back to the same partners. However, I assume that foreign firms search for the lowest-cost suppliers of the required intermediate goods.

by

$$r_n^j(\omega^j) = \left(\frac{p_n^j(\omega^j)}{P_n^j}\right)^{-\sigma^j} Q_n^j,$$

where the unit price of composite intermediate good is

$$P_n^j = \left[\int p_n^j(\omega^j)^{1-\sigma^j} d\omega^j\right]^{\frac{1}{1-\sigma^j}},$$

and $p_n^j(\omega^j)$ is the lowest price of intermediate good ω^j in country n, across all countries.

Composite intermediate goods from sector j unit priced at P_n^j are used as materials for the production of intermediate good ω^k in the amount of $m_n^{j,k}(\omega^k)$ in all sectors k and as final goods in consumption C_n^j.

There are two types of trade costs: iceberg trade costs and ad-valorem tariffs. One unit of tradable intermediate good in sector j shipped from country i to country n requires $d_{ni}^j \geq 1$ units in i, with $d_{nn}^j = 1$. Goods imported by country n from country i pay an ad-valorem tariff τ_{ni}^j. In the case of China, I first assume that $d_{CN2,CN1}^j = 1$ and $\tau_{CN2,CN1}^j = 0$, which implies China's processing firms can purchase domestic intermediate inputs with zero tariffs. Second, I assume $\tau_{CN1,CN2}^j = \infty$, which prevents processing firms from selling final goods to the domestic market.[2] Finally, I assume $\tau_{CN2,i}^j = 0$, which represents the duty-free policy on processing imports. The combined trade costs are therefore represented by

$$\kappa_{ni}^j = \tilde{\tau}_{ni}^j d_{ni}^j, \tag{3}$$

[2] In limited cases, processing firms can sell final goods to the domestic market by paying back the exempted tariffs. However, the total value of such transactions is small.

where $\tilde{\tau}^j_{ni} = (1 + \tau^j_{ni})$. For non-tradable sectors, assume that $\kappa^j_{ni} = \infty$.

After taking into account trade costs, the unit price of a tradable intermediate good ω^j produced in country i used in country n is $c^j_i \kappa^j_{ni}/z^j_i(\omega^j)$. Countries search for the lowest price supplier, therefore, the price of intermediate good ω^j in country n is given by

$$p^j_n(\omega^j) = min_i \left[\frac{c^j_i \kappa^j_{ni}}{z^j_i(\omega^j)}\right].$$

I assume the efficiency of producing ω^j in country n follows a Frechet distribution with λ^j_i being the location parameter (absolute advantage), and θ^j being the shape parameter (comparative advantage). I also assume that the distributions of productivities are independent across goods, sectors and countries. The price of the composite intermediate good is then given by

$$P^j_n = A^j [\sum_{i=1}^{N} \lambda^j_i (c^j_i \kappa^j_{ni})^{-\theta^j}]^{-1/\theta^j}, \tag{4}$$

where A^j is a constant.

Consumers purchase final goods at prices P^j_n. Using equation (1), the consumption price index is given by

$$P_n = \prod_{j=1}^{J} (P^j_n/\alpha^j_n)^{\alpha^j_n}. \tag{5}$$

Total expenditure on sector j goods in country n is given by $X^j_n = P^j_n Q^j_n$. Let X^j_{ni} be the expenditure in country n of sector j goods imported from country i. Then country n's share of expenditure on goods from country i is $\pi^j_{ni} = X^j_{ni}/X^j_n$. Following the properties of the Frechet distribution, we have

$$\pi^j_{ni} = \frac{\lambda^j_i [c^j_i \kappa^j_{ni}]^{-\theta^j}}{\sum_{h=1}^{N} \lambda^j_h [c^j_h \kappa^j_{nh}]^{-\theta^j}}. \tag{6}$$

Total expenditure on goods j is the sum of the expenditure on intermediates by firms and the expenditure by households.

$$X_n^j = \sum_{k=1}^{J} \gamma_n^{j,k} \sum_{i=1}^{N} \pi_{in}^k \frac{X_i^k}{1+\tau_{in}^k} + \alpha_n^j I_n, \tag{7}$$

where

$$I_n = w_n L_n + R_n + D_n \tag{8}$$

represents the total income in country n. Tariff revenues are represented by $R_n = \sum_{j=1}^{J} \sum_{i=1}^{N} \tau_{ni}^j M_{ni}^j$, where $M_{ni}^j = \pi_{ni}^j \frac{X_n^j}{1+\tau_{ni}^j}$ are country n's imports of sector j's goods from country i. In the case of China, as $\tau_{CN2,i}^j = 0$, processing trade does not generate any tariff revenues. The sum of trade deficit across countries is zero: $\sum_{n=1}^{N} D_n = 0$. Sectoral deficits are defined by $D_n^j = \sum_{i=1}^{N} M_{ni}^j - \sum_{i=1}^{N} E_{ni}^j$, where $E_{ni}^j = \pi_{in}^j \frac{X_i^j}{1+\tau_{in}^j}$ are country n's exports of sector j goods to country i. National deficits are the sum of sectoral deficits: $D_n = \sum_{k=1}^{J} D_n^k$. I assume that aggregate trade deficits in each country are exogenous but sectoral trade deficits are endogenous.

Finally, we have

$$\sum_{j=1}^{J} \sum_{n=1}^{N} \frac{\pi_{ni}^j X_n^j}{1+\tau_{ni}^j} - D_i = \sum_{j=1}^{J} \sum_{n=1}^{N} \frac{\pi_{in}^j X_i^j}{1+\tau_{in}^j}, \tag{9}$$

which implies that total expenditure (excluding tariff payments) in country n minus trade deficits equals the sum of each country's total expenditure (excluding tariff payments) on tradable goods from country n.

With all the setup above, the equilibrium in this model is defined as: given endowments $\{L_n\}_{n=1}^{N}$, transfers $\{D_n\}_{n=1}^{N}$, fundamentals $\{\lambda_n^j,\, d_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$, parameters $\{\gamma_n^j,\, \gamma_n^{k,j},\, \alpha_n^j\}_{n=1,k=1,j=1}^{N,J,J}$, and trade elasticities $\{\theta^j\}_{j=1}^{J}$, an equilibrium under a tariff structure $\{\tau_{ni}^j\}_{n=1,i=1,j=1}^{N,N,J}$ is a wage vector $\boldsymbol{w}$ and prices $\{P_n^j\}_{j=1,n=1}^{J,N}$that satisfies equilibrium conditions (2), (4), (6), (7), and (9) for all i and j.

3.2.2 Equilibrium in Relative Changes

Solving for an equilibrium under a tariff structure τ_{ni}^j requires knowledge of fundamentals $\{\lambda_n^j,\ d_{ni}^j\}$ which we cannot observe in the data. However, following Dekle et al. (2007) and Caliendo and Parro (2015), I can use the exact-hat algebra method which consists of writing the equilibrium conditions with the relative changes in a counterfactual tariff structure $\tau_{ni}^{j'}$. Let x be the value of endogenous variable under the actual set of fundamentals and tariff structure. And let x' be the unknown value of endogenous variable under a counterfactual tariff structure. Then $\hat{x} = x'/x$ represents the change in the equilibrium values as a result of changes in tariffs $\hat{\tau}_{ni}^j$.[3] Using this notation, the equilibrium conditions in hat-changes are given by

$$\hat{c}_n^j = \hat{w}_n^{\gamma_n^j} \prod_{k=1}^{J} [\hat{P}_n^k]^{\gamma_n^{k,j}}. \tag{10}$$

$$\hat{P}_n^j = \left[\sum_{i=1}^{N} \pi_{ni}^j [\hat{\kappa}_{ni}^j \hat{c}_i^j]^{-\theta^j} \right]^{-1/\theta^j}. \tag{11}$$

$$\hat{\pi}_{ni}^j = \left[\frac{\hat{\kappa}_{ni}^j \hat{c}_i^j}{\hat{P}_n^j} \right]^{-\theta^j}. \tag{12}$$

$$X_n^{j'} = \sum_{k=1}^{J} \gamma_n^{j,k} \sum_{n=1}^{N} \pi_{in}^{k'} \frac{X_i^{k'}}{1+\tau_{in}^{k'}} + \alpha_n^j I_n'. \tag{13}$$

[3] This method can potentially be used to back out change in fundamentals (A_n^j and d_{ni}^j) as well.

$$\sum_{j=1}^{J}\sum_{n=1}^{N}\frac{\pi_{ni}^{j'}X_n^{j'}}{1+\tau_{ni}^{j'}} - D_n = \sum_{j=1}^{J}\sum_{n=1}^{N}\frac{\pi_{in}^{j'}X_i^{j'}}{1+\tau_{in}^{j'}}, \tag{14}$$

where $\hat{\kappa}_{ni}^{j} = (1+\tau_{ni}^{j'})/(1+\tau_{ni}^{j})$ and $I_n' = \hat{w}_n w_n L_n + TR_n' + D_n = \hat{w}_n w_n L_n + \sum_{j=1}^{J}\sum_{n=1}^{N}\tau_{ni}^{j'}\pi_{ni}^{j'}\frac{X_n^{j'}}{1+\tau_{ni}^{j'}} + D_n$.

In the next section, I discuss how to take the model to the data and solve the model in relative changes.

3.3 Calibration

Solving for an equilibrium using the exact-hat algebra method requires three sets of data. First, I need data on bilateral trade shares (π_{ni}^{j}), share of value added (γ_n^j), share of intermediate inputs ($\gamma_n^{k,j}$), value added ($w_n L_n$), and share in final consumption (α_n^j), all of which can be obtained from the input-output table. Second, I need the trade elasticities θ^j. Finally, I need the tariff data in the base year (2017) and the tariffs imposed by the United States and its trading partners during the trade war. The subsections below discuss the data and the calibration in detail.

3.3.1 Inter-Country Input-Output Table

The primary database used to calibrate the model is the Inter-Country Input-Output (ICIO) table developed by the OECD for 2017. It provides comprehensive information at the country-industry level on bilateral trade flows of intermediate inputs and final goods, gross value added, and gross output. In comparison to other commonly used databases in the frontier quantitative trade literature, such as the World Input-Output Database (WIOD), the OECD ICIO has a unique feature that distinguishes

Table 3.1: Example of a Standard Input-Output Table (One Sector)

	Intermediate Input				Final Demand				
	China	Country 1	...	Country N	China	Country 1	...	Country N	Gross Outputs
China	$I_{CN,CN}$	$I_{CN,1}$	...	$I_{CN,N}$	$F_{CN,CN}$	$F_{CN,1}$	...	$F_{CN,N}$	Y_{CN}
Country 1	$I_{1,CN}$	$I_{1,1}$	...	$I_{1,N}$	$F_{1,CN}$	$F_{1,1}$	...	$F_{1,N}$	Y_1
...	...	...	...	...	...	...	...	...	...
Country N	$I_{N,CN}$	$I_{N,1}$	...	$I_{N,N}$	$F_{N,CN}$	$F_{N,1}$	...	$F_{N,N}$	Y_N
Value Added	VA_{CN}	VA_1	...	VA_N					
Gross Outputs	Y_{CN}	Y_1	...	Y_N					

non-processing production from processing production for China. This characteristic enables the calibration of separate parameters for China's processing production.

Table 3.1 illustrates the structure of a standard input-output table for one sector. It displays the trade flows of intermediate inputs and final goods, with each row representing a source country and each column representing a destination country. For instance, $I_{CN,N}$ represents the value of intermediate goods sold by China and purchased by country N, while $F_{CN,N}$ represents the value of final goods sold by China and purchased by country N. However, the World Input-Output Database (WIOD) and similar databases cannot differentiate between China's ordinary production and processing production. In contrast, the Inter-Country Input-Output (ICIO) table, which I use to calibrate the model, allows for such a distinction.

Table 3.2 presents an example of the structure of the OECD ICIO table for one sector, which considers the heterogeneity of production in China by splitting its IO tables into two different structures. The table distinguishes between China's non-processing (ordinary) production and processing production, labeled as China (1) and China (2), respectively. The values in the table show the trade flows in intermediate inputs and final goods between the two types of production in China and other countries. For example, $I_{CN1,CN2}$ is the value of intermediate goods from China's non-processing (ordinary) production being used by China's processing production,

Table 3.2: Example of the OECD ICIO Table (One Sector)

	Intermediate Input				Final Demand				
	China (1)	China (2)	...	Country N	China (1)	China (2)	...	Country N	Gross Outputs
China (1)	$I_{CN1,CN1}$	$I_{CN1,CN2}$	...	$I_{CN1,N}$	$F_{CN1,CN1}$	$F_{CN1,CN2}$	...	$F_{CN1,N}$	Y_{CN1}
China (2)	$I_{CN2,CN1}$	$I_{CN2,CN2}$	...	$I_{CN2,N}$	$F_{CN2,CN1}$	$F_{CN2,CN2}$	...	$F_{CN2,N}$	Y_{CN2}
...	...	...	...	...	...	...	...	...	...
Country N	$I_{N,CN1}$	$I_{N,CN2}$	...	$I_{N,N}$	$F_{N,CN1}$	$F_{N,CN2}$	...	$F_{N,N}$	Y_N
Value Added	VA_{CN1}	VA_{CN2}	...	VA_N					
Gross Outputs	Y_{CN1}	Y_{CN2}	...	Y_N					

and $F_{CN2,N}$ is the value of final goods from China's processing production being bought by country N.

Intuitively, the OECD ICIO table treats China as two separate economies, with distinct trade flows in intermediate inputs and final goods with all other countries. This allows for the calibration of the parameters for China's processing production separately from its non-processing production. The data is derived from an extended China's national input-output table that accounts for the dual trade regimes in China. This extended IO framework was built on China's standard national IO table, supplemented with microdata such as the manufacturing firm surveys and detailed customs data, and provided by a research team from the Chinese Academy of Sciences and the National Bureau of Statistics.[4]

To calibrate the model with the OECD ICIO table, there are two notable features to consider. First, goods from $CN2$ cannot be used as intermediate inputs or final consumption in $CN1$, which means that $I_{CN2,CN1} = F_{CN2,CN1} = 0$. However, $CN2$ can import intermediate inputs from $CN1$. Second, $CN2$ does not consume any final goods, so $F_{CN2} = 0$ for all sectors. Based on these features, the model is calibrated with 44 countries (including two China and the rest of the world) and 45 industries, 21 of which are tradable and 24 non-tradable. The names and ICIO codes of the

[4] For more detail, please see Chen et al. (2019) and Chen et al. (2020).

Table 3.3: Codes and Names of Tradable Sectors

Code	Industry	ISIC Rev.4
D01T02	Agriculture	01, 02
D03	Fishing	3
D05T06	Mining (energy)	05, 06
D07T08	Mining (non-energy)	07, 08
D10T12	Food	10, 11, 12
D13T15	Textile	13, 14, 15
D16	Wood	16
D17T18	Paper	17, 18
D19	Petroleum	19
D20	Chemicals	20
D21	Medical	21
D22	Plastics	22
D23	Minerals	23
D24	Basic Metals	24
D25	Metal Products	25
D26	Computer (office)	26
D27	Electrical	27
D28	Machinery n.e.c	28
D29	Auto	29
D30	Other Transport	30
D31T33	Other	31, 32, 33

21 tradable industries in the sample are summarized in Table 3.3, in which each industry is identified according to its covered sub-industries' ISIC Rev.4 codes. A detailed description of each industry is listed in Table A3 in the Appendix, and all the countries in the sample are listed in Table A4.

3.3.2 Trade Elasticity

The trade elasticities θ^j are the key parameters to estimate the effects of tariff changes. The trade elasticities in this model are related to the dispersion of productivity.[5] If productivity is more concentrated, as indicated by a larger value of θ^j, the change in share of traded goods will be relatively small in response to changes in tariffs. If productivity is more dispersed, small changes in tariffs can result in large adjustments in the share of goods traded. Intuitively, with smaller θ^j , producers will be more likely to change their suppliers (source from a different country) in response to tariff changes.

In this chapter, I map the trade elasticities from Caliendo and Parro (2015) to the tradable sectors in my sample. Table 3.4 shows the corresponding elasticities.

3.3.3 Sectoral Tariff Changes

To construct the sectoral tariff changes during the trade war, I collect tariffs and trade data from multiple sources. As mentioned in Chapter 2, the Chinese retaliatory tariffs are obtained from the Ministry of Finance of China. To aggregate the retaliatory tariffs from HS-8 tariff lines to 21 tradable sectors in my sample, I use a concordance table to ISIC Rev.4 and the non-processing import shares in 2017, which are calculated from the Chinese Customs data, as weights.

Figure 3.1 illustrates the changes in tariffs applied by China due to the trade war. The dark grey bar represents the changes in tariffs using the shares of ordinary

[5] In this model, the elasticity of trade with respect to trade costs is the dispersion of productivity, rather than the elasticity of substitution as in Armington models (Caliendo and Parro 2015). In Armington models, goods are always bought from all countries as goods are differentiated by country of origin. In this model, the source of goods can change as a consequence of tariff reductions. Therefore, tariff changes can result in both changes in the extensive margin as well as intensive margin.

Table 3.4: Trade Elasticities

Industry	$\hat{\theta}^j$	Industry	$\hat{\theta}^j$
Agriculture	9.11	Plastics	1.67
Fishing	9.11	Minerals	2.41
Mining (energy)	13.53	Basic Metals	3.28
Mining (non-energy)	13.53	Metal Products	6.99
Food	2.62	Computer (office)	12.95
Textile	8.10	Electrical	12.91
Wood	11.50	Machinery n.e.c	1.45
Paper	16.62	Auto	1.84
Petroleum	64.85	Other Transport	0.39
Chemicals	3.13	Other	3.98
Medical	8.71		

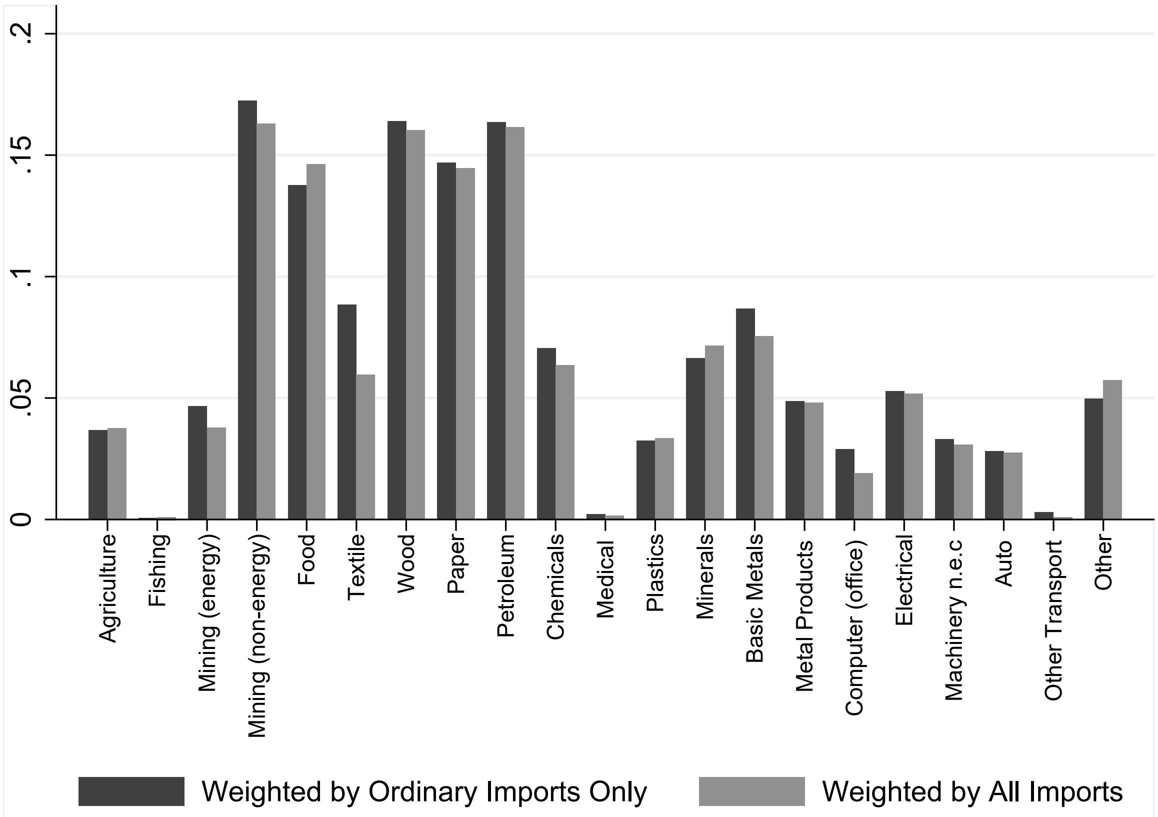
Notes: Trade elasticities are mapped from Caliendo and Parro (2015).

imports as weights, while the light grey bar displays the tariff changes using the shares of all Chinese imports as weights.

The trade war tariffs imposed by the United States on Chinese products at HS-10 level are collected from Fajgelbaum et al. (2020). Baseline tariffs for the U.S. are obtained from the World Integrated Trade Solution (WITS) for the year 2017. The import shares in 2017, calculated from the U.S. census data, are used as weights to aggregate product-level tariffs to the sectors in the sample. Figure 3.2 displays the changes in tariffs applied by the United States to China across industries. The trade-weighted U.S. tariffs on Chinese products are significantly higher than the Chinese retaliatory tariffs in almost all industries.

Additionally, I gather the retaliatory tariffs enforced by other U.S. trading partners from Fajgelbaum et al. (2020). For all other countries in my sample, the original bilateral tariffs and import values at HS-6 level are collected from WITS for the year 2017. Then, I use the same approach to calculate the trade-weighted average tariffs

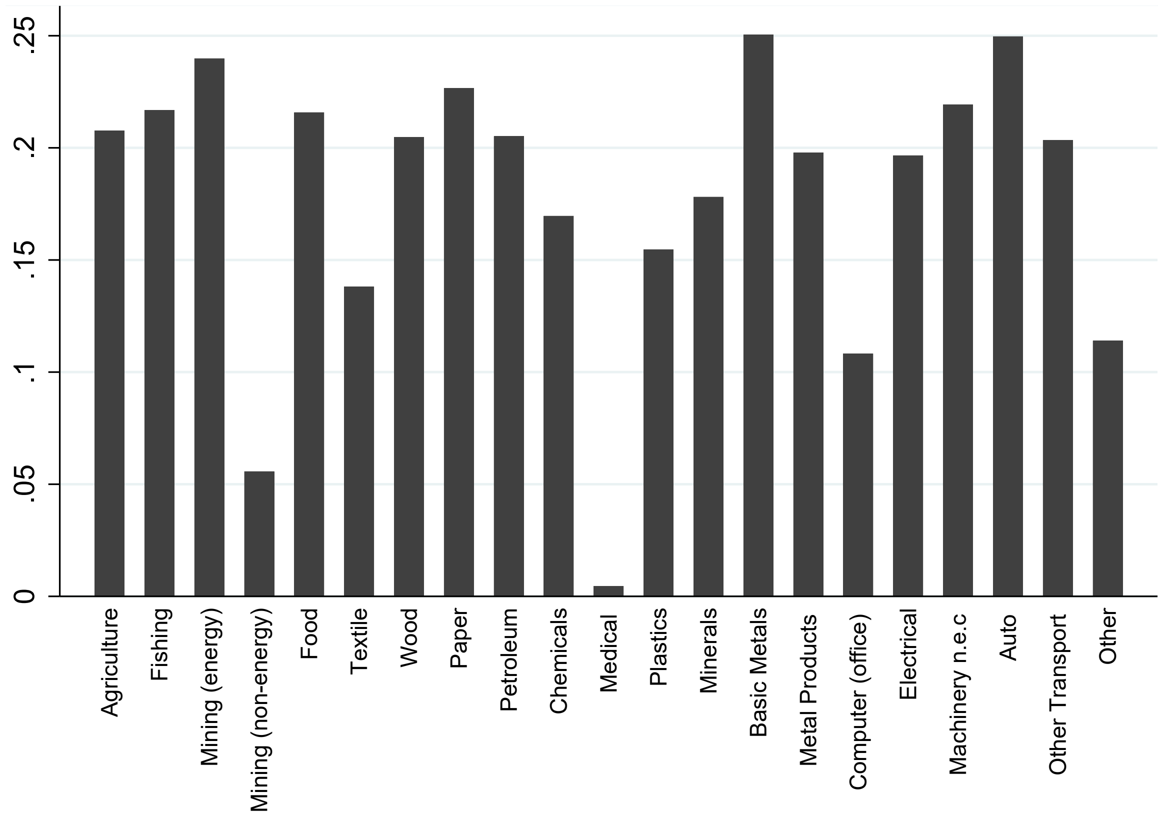
Figure 3.1: Changes in Tariffs Applied by China to the U.S.



Notes: Figure 3.1 displays the changes in trade-weighted average tariffs applied by China to the U.S. during the trade war. The Chinese retaliatory tariffs at HS-8 level are obtained from the Ministry of Finance of China and are mapped to the industries in the sample using a concordance table to ISIC Rev.4. The import shares in 2017 from the Chinese Customs data are used as weights to calculate the trade-weighted average tariffs. The vertical axis shows the percentage point changes, while the horizontal axis represents the industries. The dark grey bar indicates the changes in tariffs using the shares of ordinary imports as weights, and the light grey bar shows the tariff changes using the shares of all Chinese imports as weights.

at the sectoral level.

Figure 3.2: Changes in Tariffs Applied by the U.S. to China



Notes: Figure 3.2 displays the changes in trade-weighted average tariffs applied by China to the U.S. during the trade war. The HS-10 level U.S. tariffs are obtained from Fajgelbaum et al. (2020), and a concordance table is used to map HS-10 to ISIC Rev.4 and then to the sectors in the sample. The trade-weighted average tariffs are calculated using the import shares in 2017 obtained from the U.S. census data as weights. The horizontal axis represents the industries, while the vertical axis shows the percentage point changes in the trade-weighted average tariffs.

3.3.4 Taking the Model to the Data

With data on trade elasticities θ^j and bilateral tariffs τ_{ni}^j in hand, I can use the OECD ICIO table to calculate the data counterparts to calibrate the model. In particular, the data needed are gross output (Y_n^j), bilateral trade flow (M_{ni}^j and E_{ni}^j), value added (VA_n^j), bilateral trade share (π_{ni}^j), share of value added (γ_n^j), share of intermediate consumption ($\gamma_n^{j,k}$), and final consumption share (α_n^j).

The value of Y_n^j, M_{ni}^j, E_{ni}^j and VA_n^j can be directly extracted from the ICIO table. To obtain the bilateral trade share π_{ni}^j, I first calculate domestic sales in each country, M_{nn}^j as the differences between gross output and total exports: $M_{nn}^j = Y_n^j - \sum_{i=1,i\neq n}^N E_{ni}^j$. Then I calculate the expenditure that country n of sector j goods imported from country i (X_{ni}^j) by multiplying imports by tariffs: $X_{ni}^j = M_{ni}^j \times (1+\tau_{ni}^j)$. The bilateral trade share is calculated as $\pi_{ni}^j = X_{ni}^j / \sum_{i=1}^N X_{ni}^j$. The share of value added in each sector and country is calculated as $\gamma_n^j = VA_n^j / Y_n^j$. To calculate the share of country n sector k's spending on sector j's good ($\gamma_n^{j,k}$), I first calculated the share of intermediate consumption of sector j in sector k over the total intermediate consumption of sector k in country n. Then I multiply it by one minus the share of value added in sector j, $1-\gamma_n^j$, to normalize it so that $\sum_{j=1}^J \gamma_n^{j,k} + \gamma_n^j = 1$. Finally, to calculate the final consumption share α_n^j, I take country n's total expenditure of sector j goods, subtract the intermediate goods expenditure and divide by total final absorption: $\alpha_n^j = (Y_n^j + D_n^j - \sum_{k=1}^J \gamma_n^{j,k} Y_n^k)/I_n$, where I_n is given by equation (8) and sectoral trade deficits are defined by $D_n^j = \sum_{i=1}^N M_{ni}^j - \sum_{i=1}^N E_{ni}^j$.

It is worth highlighting that China's processing production (denoted by $CN2$) should generate zero income under the definition from this model and the structure of the ICIO table.[6] To see this, recall that $I_{CN2} = w_{CN2}L_{CN2} + R_{CN2} + D_{CN2} = VA_{CN2} + R_{CN2} + (M_{CN2} - E_{CN2})$. By definition, $R_{CN2} = 0$ as there is no tariff. Moreover, since all the imports, both goods and services, are used as intermediate inputs and then exported after adding value, $E_{CN2} - M_{CN2} = VA_{CN2}$, and therefore $I_{CN2} = 0$. This further implies that there should not be any change in real income due to changes in tariffs. However, when mapping the data to the model, I cannot

[6] However, $CN2$ does generate positive labor income.

perfectly distinguish tradable services from non-tradable services as there are only 24 aggregated service industries in the ICIO table. As a result, by assuming that all services are non-tradable, M_{CN2} will be smaller than in reality as some services are being imported as intermediate inputs, leading to non-zero incomes for $CN2$. An ideal way to resolve this issue is to use a dataset that can perfectly distinguish tradable services from non-tradable services so that I can allow some service industries to be tradable.[7] However, given the data limitation, I report the changes in real income generated by China's ordinary production in the result section to prevent the inconsistency between the model and the data from complicating the interpretation of the estimated welfare effects. I present a more detailed description of this issue and discuss its potential implications in the Appendix.

3.3.5 Solving the Model for Tariff Changes

I follow Caliendo and Parro (2015) to solve the model using the calibrated parameters and equation (10)-(14). An issue in the computation of counterfactuals is the treatment of trade imbalances D_i. Since the model is calibrated to match the base year (2017), the country-aggregate trade deficits are exogenous in the model, and changes in tariffs will not change the aggregate trade deficit in the counterfactual. Therefore, I follow Dekle et al. (2007) and Caliendo and Parro (2015) to calibrate the model with aggregate deficits to the year 2017 and then calculate all counterfactuals assuming that countries' aggregate deficits are constant relative to world GDP and lump-sum transferred to consumers.

When solving the model, I also assume that the wages are the same for China's

[7] This will also require elasticity estimates for tradable service industries.

ordinary and processing production in the base year as they share the same labor market. However, I allow the wages to be different in the counterfactuals which implicitly assumes that labor are immobile between $CN1$ and $CN2$ in the short-run.

3.4 Results

This section describes the estimation results from the quantitative model. In order to explore the role of China's duty-free policy on processing imports during the 2018-2019 trade war, I present two sets of results. The first set considers China as a single economy, where all imports are subject to the same tariffs, regardless of whether they are for processing or non-processing production.[8] The second set of results treats China as two separate economies, with one engaging only in processing production and the other only in non-processing production. By doing so, only China's non-processing imports are subject to the retaliatory tariffs (although all China's exports are subject to the same U.S. tariffs when exporting). By comparing the results between these two sets, I highlight the importance of China's duty-free policy on processing imports and its impact in the presence of the trade war.

Table 3.5 shows the effects of the 2018-2019 trade war for China and the U.S. in terms of changes in real wages ($\hat{w}_n/\hat{P}_n$) and changes in real income ($\hat{I}_n/\hat{P}_n$). I find that the exemption of processing imports from tariffs through China's duty-free policy played a significant role in reducing China's welfare loss during the trade war. In the counterfactual regime where processing imports were not exempted from tariffs, the trade war would have resulted in a 0.13% decrease in real wages in China and a

[8] I aggregate the data from the ICIO table and assume that all China's processing imports are subject to the same tariffs as ordinary imports.

Table 3.5: Welfare Effects of the 2018 Trade War

	With Processing Trade (Actual Regime)		Without Processing Trade (Counterfactual Regime)	
	Real Wages	Real Income	Real Wages	Real Income
China	-0.09%	-0.10%	-0.13%	-0.18%
United States	-0.15%	0.04%	-0.15%	0.03%

Notes: Column (1)-(2) report total import quantities and values from all third countries other than the U.S. regressed on trade weighted Chinese retaliatory tariffs at HS-6 level. The changes are from 2017 Q4 to 2019 Q4. Both regressions include product fixed effects at the HS-2 level. Robust standard errors in the parentheses are clustered at HS-6. Significance: * 0.10, ** 0.05, *** 0.01.

0.15% decrease in the United States. After accounting for changes in tariff revenues, I find that real income in China decreased by 0.18%, while in the United States, it slightly increased by 0.03%. In contrast, after accounting for processing imports, the decrease in real wages and real income in China were 0.09% and 0.1%, respectively. This indicates that the duty-free policy on processing imports reduced the loss in real wages by 30% and the loss in real income by 44%. These findings align with those of Caliendo and Parro (2021), who found that the decline in real wages and real income in China would have been smaller if China had not retaliated.

Table 3.5 only presents the welfare effects associated with China's non-processing production. This is because, as discussed in the previous section, if the data could perfectly distinguish between tradable and non-tradable services, the income generated by China's processing production should be zero both before and after the trade war. However, due to data limitations, Table A5 in the Appendix shows that the changes in real wages for China's processing production are close to zero, and the real income generated by China's processing production increased by 10.2%.

Calculating the aggregate welfare effects for the sum of fictional Chinese economies is challenging. One reasonable approach involves using the populations of both economies as weights to compute the weighted average, which results in nearly zero loss in aggregate real income for China. Although the model does not directly observe each economy's population, it can be estimated using wages and observed value-added. Another method involves adding the labor income generated by China's processing production to the total income generated by China's ordinary production, and then dividing the aggregate income change by the change in the price index in "ordinary China" which can be expressed as $\hat{I}_{CN}/\hat{P}_{CN} = (\widehat{I_{CN1} + w_{CN2}}L_{CN2})/\hat{P}_{CN1}$.[9] As the change in real wages for $CN2$ is minimal, this method produces results similar to those reported in Table 3.5.

Intuitively, China's duty-free policy on processing imports acts like exemptions of the retaliatory tariffs. To account for China's duty-free policy on processing imports, we expect industries with a predominant share of processing production to be less affected by the trade war. Table 3.6 provides sectoral contributions to China's aggregate welfare effects in terms of changes in real income. The aggregate change can be explained by a handful of industries, but there is considerable variation across industries. Without considering processing imports, Computer, Electrical, and Textile industries are the top three contributors to China's real income loss, accounting for 42% of the reduction. Among them, the Computer industry alone contributes to an 18.36% reduction in China's real income. However, after accounting for processing imports, the Computer industry's contribution to China's real income loss drops to 7.12%. It is worth noting that Table 3.6 reports estimates for "ordinary China" only. Table A6 in the Appendix provides the sectoral contributions to welfare effects for "processing China" only, showing that the top three contributors to China's real in-

[9] Again, here I assume that labor are fixed between $CN1$ and $CN2$ in the counterfactuals.

Table 3.6: Sectoral Contribution to Welfare Effects for China

Industry	With Processing Trade (Actual Regime)	Without Processing Trade (Counterfactual Regime)
Agriculture	7.33%	5.51%
Fishing	0.25%	0.18%
Mining (energy)	-0.27%	-0.18%
Mining (non-energy)	-0.78%	-0.49%
Food	6.20%	4.82%
Textile	16.13%	14.17%
Wood	1.02%	0.56%
Paper	1.45%	1.00%
Petroleum	4.45%	3.20%
Chemicals	7.26%	5.63%
Medical	1.27%	1.27%
Plastics	3.41%	3.00%
Minerals	3.28%	2.44%
Basic Metals	6.60%	3.76%
Metal Products	6.36%	4.90%
Computer (office)	7.12%	18.36%
Electrical	7.53%	9.71%
Machinery n.e.c	7.38%	7.76%
Auto	5.97%	5.01%
Other Transport	2.32%	2.86%
Other	5.70%	6.57%
Total	100%	100%

Notes: Table 3.6 presents the sectoral contribution to changes in real income in China due to the 2018-2019 trade war. The second column shows the contribution of each sector in the actual regime, taking into account China's duty-free policy on processing imports, while the third column shows the sectoral contribution in the counterfactual regime where the policy is not considered.

come gain in processing production are Computer (55.76%), Electrical (15.06%), and Machinery n.e.c (7.27%).

The results suggest that industries with prevalent processing trade are the primary drivers of significant changes in welfare effects. As shown in Table 3.7, the

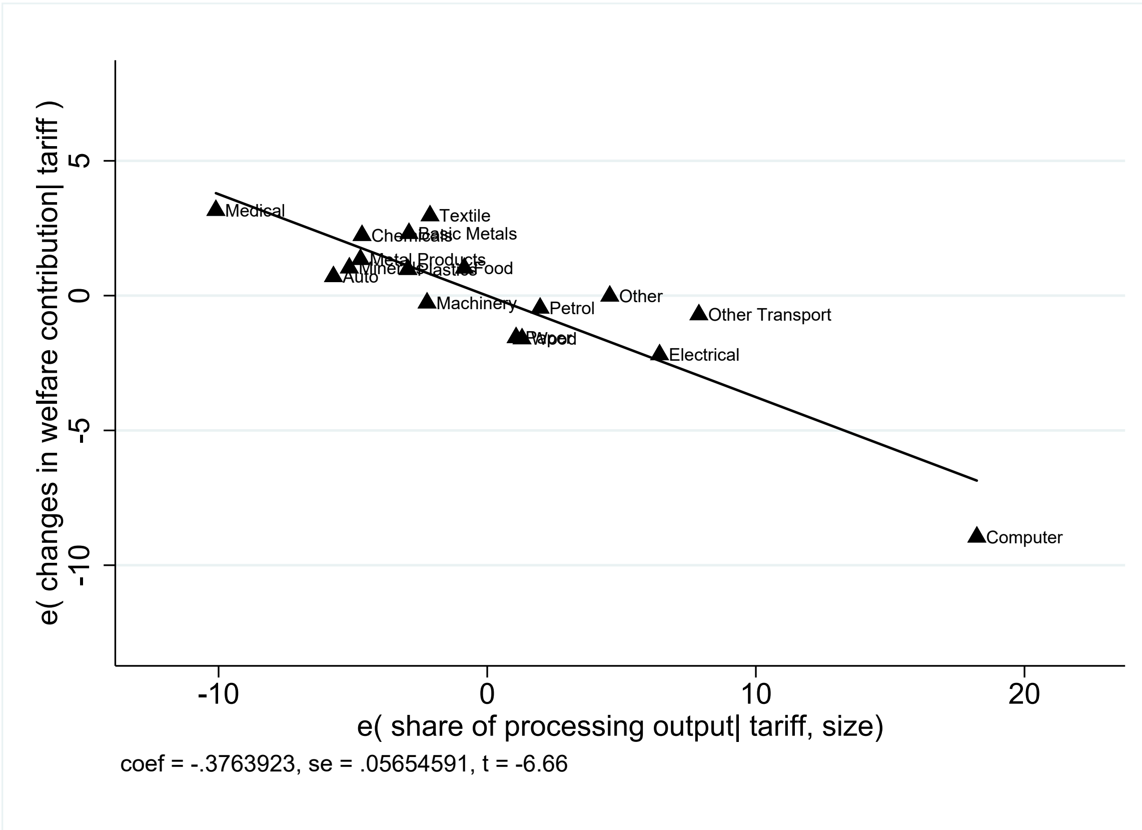
Table 3.7: Share of Processing Output across China's Manufacturing Industries

Industry	Processing Output	Total Output	Processing Output Share
Food	5.97	1723.20	0.35%
Textile	37.56	1282.79	2.93%
Wood	0.91	207.98	0.44%
Paper	3.67	406.37	0.90%
Petroleum	7.08	546.47	1.30%
Chemicals	9.56	1182.00	0.81%
Medical	5.28	334.99	1.58%
Plastics	22.11	482.32	4.55%
Minerals	2.35	865.62	0.27%
Basic Metals	6.87	1515.08	0.45%
Metal Products	8.35	674.90	1.24%
Computer (office)	377.01	1387.30	27.18%
Electrical	98.13	802.55	12.23%
Machinery n.e.c	46.27	1046.16	4.42%
Auto	8.13	1107.77	0.73%
Other Transport	30.91	192.50	16.06%
Other	38.67	330.30	11.71%

Notes: Table 3.7 presents the share of processing output in China's manufacturing industries. The second column displays the value of processing output in billion USD, while the third column shows the value of China's gross output in each industry. The last column indicates the share of processing production in total output across industries.

Computer industry is the largest processing industry in terms of output value, accounting for 27% of China's gross output in this industry. Conversely, processing output only accounts for less than 3% of China's total output in the Textile industry, resulting in a small change in sectoral contribution when considering processing imports. Other factors that may explain the differences in sectoral contribution include the magnitude of trade war tariffs and the size of industries, as measured by the value of total output. For instance, the Other Transport industry has a processing output accounting for 16% of China's gross output, yet Figure 3.1 indicates that the trade-

Figure 3.3: Conditional Correlation Between Changes in Welfare Contribution and Share of Processing Output (China)



Notes: Figure 3.3 displays the added variable plot showing the coefficient, robust standard error, and fitted line from an OLS regression. The horizontal axis is the expectation of the share of processing output across China's manufacturing industries, conditional on the size, Chinese retaliatory tariffs, and U.S. tariffs of each industry. The vertical axis is the expectation of the differences in the welfare contribution between the actual and counterfactual regimes for China, conditional on the size, Chinese retaliatory tariffs, and U.S. tariffs of each industry.

weighted average Chinese retaliatory tariffs on this industry were close to zero. This suggests that non-processing imports in this industry were not subject to significant tariff increases, while the industry's relatively small size may partially account for its minimal contribution to China's welfare loss.

To highlight the importance of processing trade, Figure 3.3 displays an added variable plot illustrating the conditional correlation between the share of processing output and the differences in sectoral welfare contribution between the actual and counterfactual regimes, while controlling for the industry sizes and the trade war tariffs. The differences in sectoral welfare contribution are obtained by subtracting the contribution in the counterfactual regime from that in the actual regime. For example, the difference for the Computer industry is $7.12 - 18.36 = -11.24$. Using a regression model, I examine the relationship between the calculated differences and the share of processing output, industry size, Chinese retaliatory tariffs, and U.S. tariffs. While the plot does not imply causality, it shows that industries with a higher share of processing output tend to exhibit more significant differences in welfare contribution between the actual and counterfactual regimes.

Table 3.8 presents the sectoral contribution to welfare effects for the U.S. Intuitively, without China's duty-free policy on processing imports, Chinese retaliatory tariffs can lead to more significant increases in the cost of intermediate inputs for some products and increase the prices of exports. The U.S. may also suffer from the Chinese retaliatory tariffs as it might have to pay higher prices on imported goods depending on the tariff pass-through rate. Although the overall gain in real income is minimal for the U.S., taking China's duty-free policy on processing imports into account still leads to changes in the sectoral contribution. Table 3.8 shows that without China's duty-free policy on processing imports, the Computer industry contributes the most to the U.S. gain in real income with 28%. When the policy is being taken into account, Computer industry, where China's processing production is predominant, contributes even more with nearly 40%.

Figure 3.4 depicts the added variable plot for the United States using a similar specification as Figure 3.3. It shows that China's duty-free policy on processing

Table 3.8: Sectoral Contribution to Welfare Effects for the United States

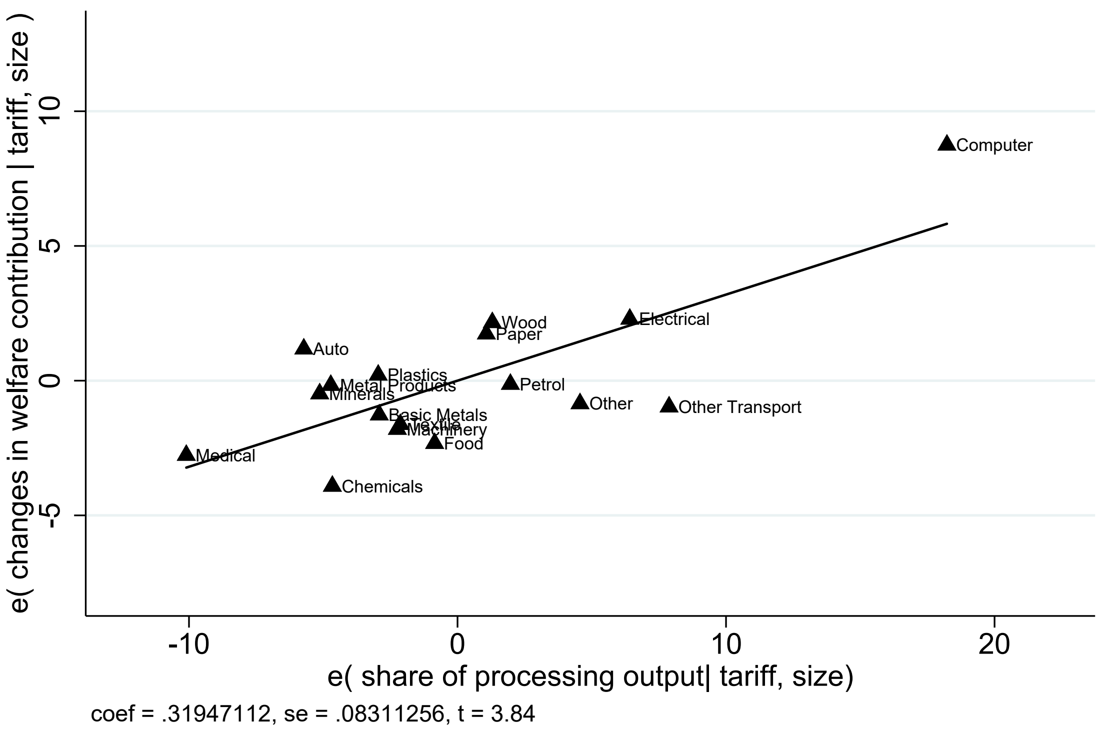
Industry	With Processing Trade (Actual Regime)	Without Processing Trade (Counterfactual Regime)
Agriculture	3.68%	5.00%
Fishing	0.36%	0.47%
Mining (energy)	0.38%	0.44%
Mining (non-energy)	0.55%	0.74%
Food	-1.10%	-0.66%
Textile	-13.07%	-13.86%
Wood	-0.08%	0.01%
Paper	1.96%	2.43%
Petroleum	4.42%	5.82%
Chemicals	8.02%	10.59%
Medical	4.27%	4.28%
Plastics	2.56%	2.73%
Minerals	-0.41%	-0.14%
Basic Metals	2.90%	3.77%
Metal Products	2.04%	3.04%
Computer (office)	39.63%	27.51%
Electrical	3.45%	1.59%
Machinery n.e.c	12.57%	14.65%
Auto	6.82%	6.47%
Other Transport	12.40%	15.79%
Other	8.64%	9.32%
Total	100%	100%

Notes: Table 3.8 presents the sectoral contribution to changes in real income in the U.S. due to the 2018-2019 trade war. The second column shows the contribution of each sector in the actual regime, taking into account China's duty-free policy on processing imports, while the third column shows the sectoral contribution in the counterfactual regime where the policy is not considered.

imports not only has an impact on itself but also has spillover effects on the U.S. welfare in the presence of the trade war.

I also use the model to estimate the trade war's trade effects for China and the U.S. across industries, computed as the percentage changes in total imports and exports

Figure 3.4: Conditional Correlation Between Changes in Welfare Contribution and Share of Processing Output (United States)

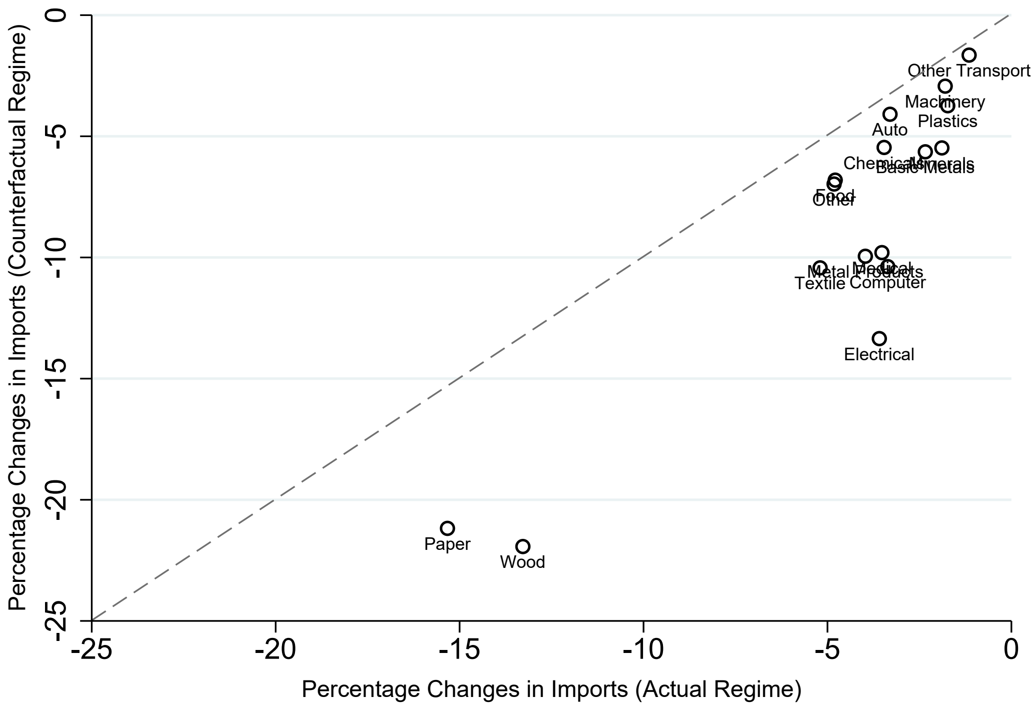


Notes: Figure 3.4 displays the added variable plot showing the coefficient, robust standard error, and fitted line from an OLS regression. The horizontal axis is the expectation of the share of processing output across China's manufacturing industries, conditional on the size, Chinese retaliatory tariffs, and U.S. tariffs of each industry. The vertical axis is the expectation of the differences in the welfare contribution between the actual and counterfactual regimes for the U.S., conditional on the size, Chinese retaliatory tariffs, and U.S. tariffs of each industry.

for each industry.[10] Table A7 in the Appendix reveals that China's aggregate imports would have decreased by 9.3%, and exports by about 7%, if processing imports had not been exempted from tariffs. In contrast, I find that China's aggregate imports

[10]Here, I report the aggregated results for China. The imports and exports from China's processing and non-processing production are added together.

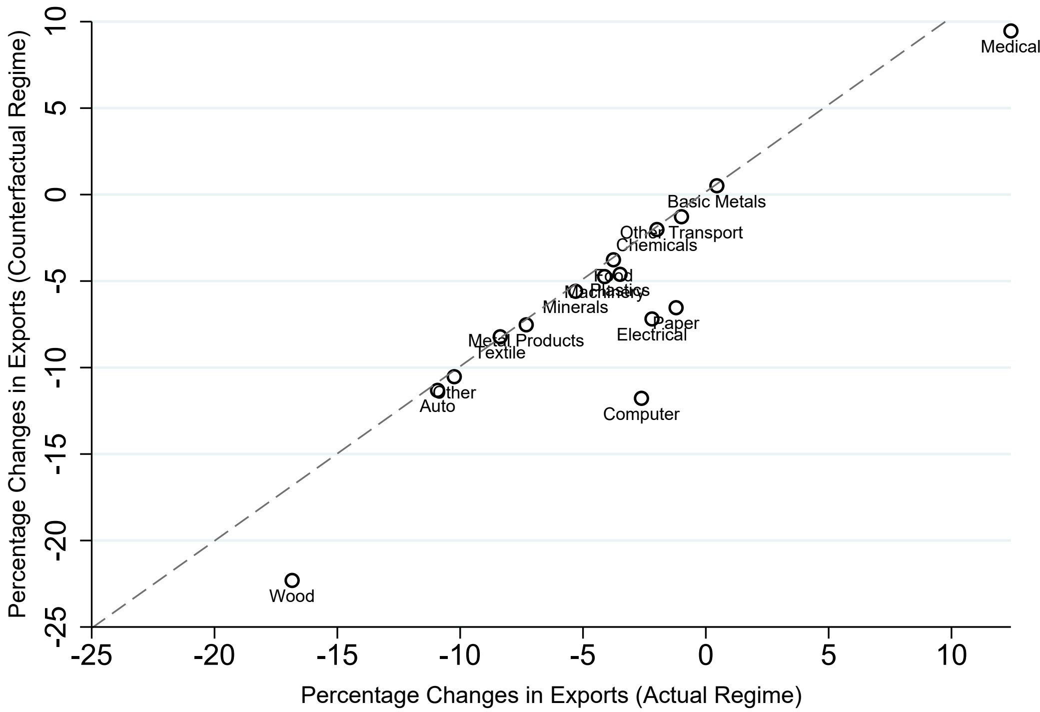
Figure 3.5: Changes in Chinese Imports across Manufacturing Industries



Notes: Figure 3.5 shows the estimated changes in imports across Chinese manufacturing industries due to the trade war. The horizontal axis represents the changes in the actual regime, taking into account China's duty-free policy on processing imports. The vertical axis represents the changes in the counterfactual regime where the policy is not considered. The grey dashed line represents the 45-degree line. All manufacturing industries are included except the Petroleum industry.

decreased only by 4.4%, and exports by 3.5% under the duty-free policy on processing imports. The decline in imports is 53% smaller, and the decline in exports is 50% smaller, similar to the changes in welfare effects. To visualize the heterogeneous impacts on different industries, Figures 3.5 and 3.6 display the estimated changes in Chinese imports and exports, respectively. The horizontal axis in both figures represents the changes in the actual regime, where processing imports are exempt

Figure 3.6: Changes in Chinese Exports across Manufacturing Industries



Notes: Figure 3.6 shows the estimated changes in exports across Chinese manufacturing industries due to the trade war. The horizontal axis represents the changes in the actual regime, taking into account China's duty-free policy on processing imports. The vertical axis represents the changes in the counterfactual regime where the policy is not considered. The grey dashed line represents the 45-degree line. All manufacturing industries are included except the Petroleum industry.

from tariffs, and the vertical axis represents the changes in the counterfactual regime. These figures suggest that both Chinese imports and exports would have experienced a more significant decline in nearly every industry if there was no duty-free policy on processing trade. For example, the Computer industry would have seen an approximately 10% decline in both imports and exports if there was no duty-free policy on processing imports. However, with this policy, the Computer industry only experienced an approximately 3% decline in imports and exports. Similar results can be found in other industries such as Electrical. These results suggest that the duty-free policy on processing imports not only protected China's imports during the trade war but also served as a built-in mechanism that prevented the Chinese retaliatory tariffs from backfiring on exports, which is one primary driver of China's economic growth. It is also worth emphasizing that in this model, sectoral trade effects are not only impacted by the size of tariff changes but also by how linked an industry is with other industries through the input-output linkages and global supply chains.

Table A8 in the Appendix displays the trade effects of the 2018 trade war in the U.S. across manufacturing industries. I find that U.S. aggregate imports declined by 5.4%, and exports by about 9.9%. These results are consistent with Caliendo and Parro (2021) in which they find the U.S. experienced a 6.5% decline in manufacturing imports and a 9.9% decline in manufacturing exports. I also find very heterogeneous sectoral effects across industries. However, taking China's duty-free policy on processing imports into account does not significantly change the estimated trade effects for the U.S.

3.5 Conclusion

Evaluating the consequences of the 2018-2019 trade war has attracted considerable attention in recent economic literature. However, a critical institutional feature has been overlooked that can lead to biases in assessing welfare effects. Approximately 40% of Chinese imports are processing imports of intermediate inputs used in export-oriented products and pay zero tariffs, even during the trade war.

Guided by the reduced-form findings in Chapter 2, I incorporate China's duty-free policy on processing imports in a quantitative general equilibrium model with sectoral linkages, trade in intermediate goods, and sectoral heterogeneity in production to quantify the welfare and trade effects of the trade war. The results reveal that China's welfare loss would have been significantly larger if China had not exempted processing imports from tariffs. The model also suggests that the duty-free policy on processing imports serves as a built-in mechanism that protected China's imports during the trade war and prevented the retaliatory tariffs from backfiring on exporting in the presence of global value chains. Finally, this chapter shows that the duty-free policy has considerable spillover effects on sectoral outcomes for the U.S.

It is important to clarify that China's duty-free policy on processing imports should not impact models that estimate trade elasticities using the changes in U.S. tariffs—for instance, neglecting the processing regime does not bias the import demand elasticities estimates of Fajgelbaum et al. (2020). With more comprehensive data, future research could explore how this policy affects China's industry-level employment and its potential impact on China's position in global value chains. The reallocation of production among different trade regimes in China would also be a valuable topic for future research.

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Appendices

Appendix for Chapter 2

Preexisting Trends

The reduced-form estimations in section 2.4 treat the tariff changes during the trade war as exogenous and assume that the changes are uncorrelated with potential demand and supply shocks. To support this identification assumption, I test the pre-trends by regressing the import outcomes before the trade war (i.e., year 2017) on the subsequent tariff changes. The equation I estimate is as following:

$$\Delta_{\overline{2017}} log[z_{ic}] = \eta \Delta_{2018-2019} log(1+\tau_{ic}) + f_i + f_c + \epsilon_{ic},$$

where $z \in \{q,\ p{\times}q,\ p,\ p\} \equiv$ {import quantity, total import value, duty-exclusive unit value, duty-inclusive unit value}. The left hand side is the average monthly change of each of four outcomes from 2017:1-2017:12. $\Delta_{2018-2019} log(1+\tau_{ic})$ represents the net log changes in import tariff rates for product i from country c between 2018:1 and 2019:12. The regression control for HS-8 product and country fixed effects. Robust standard errors are two-way clustered by country and HS-8.

Table A1 reports the estimation results and it shows there is no statistical sig-

Table A1: Testing for Preexisting Trends

	$\Delta_{\overline{2017}} lnq_{ic}$ (1)	$\Delta_{\overline{2017}} lnp^*_{ic}q_{ic}$ (2)	$\Delta_{\overline{2017}} lnp^*_{ic}$ (3)	$\Delta_{\overline{2017}} lnp_{ic}$ (4)
$\Delta_{2018-2019} log(1+\tau_{ic})$	0.12	0.15	0.03	0.03
	(0.11)	(0.11)	(0.07)	(0.07)
Product FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
R^2	0.08	0.08	0.08	0.08
N	98,264	98,264	98,264	98,264

Notes: Column (1)-(4) reports pretrend test regressions of the 2017:1-2017:12 average monthly changes in import quantities, values, before-duty unit values, after-duty unit values against net changes in Chinese import tariffs from 2018:1-2019:12. All regressions include product and country fixed effects. Robust standard errors in the parentheses are clustered by country and HS-8. Significance: * 0.10, ** 0.05, *** 0.01.

nificant relationship between pre-trend outcomes and the subsequent Chinese import tariffs.

Trade Diversion

Table A2: Trade Diversion Effect Heterogeneity

	Δlog(RoW Quantity) (1)	Δlog(RoW Quantity) (2)
$\Delta log(1 + Tariff_i^{CHN})$	-0.33	-0.54*
	(0.38)	(0.29)
$\Delta log(1 + Tariff_i^{CHN})\times$ Rauch (0/1)	0.08	
	(0.39)	
$\Delta log(1 + Tariff_i^{CHN})\times$ Soderbery (2018)		0.00
		(0.01)
Product FE (HS-2)	Y	Y
R^2	0.05	0.05
N	3,802	3,267

Notes: Column (1)-(2) report total import quantities and values from all third countries other than the U.S. regressed on trade weighted Chinese retaliatory tariffs at HS-6 level interacts with Rauch classification (Rauch 1999) and Soderbery elasticities (Soderbery 2015). The changes are from 2017 Q4 to 2019 Q4. Both regressions include product fixed effects at HS-2 level. Robust standard errors in the parentheses are clustered at HS-6. Significance: * 0.10, ** 0.05, *** 0.01.

Appendix for Chapter 3

Additional Data Description

Table A3: Tradable and Non-tradable Sectors

Number	Code	Industry	Description	ISIC Rev.4
1	D01T02	Agriculture	Agriculture, hunting, forestry	01, 02
2	D03	Fishing	Fishing and aquaculture	3
3	D05T06	Mining (energy)	Mining and quarrying, energy producing products	05, 06
4	D07T08	Mining (non-energy)	Mining and quarrying, non-energy producing products	07, 08
5	D10T12	Food	Food products, beverages and tobacco	10, 11, 12
6	D13T15	Textile	Textiles, textile products, leather and footwear	13, 14, 15
7	D16	Wood	Wood and products of wood and cork	16
8	D17T18	Paper	Paper products and printing	17, 18
9	D19	Petroleum	Coke and refined petroleum products	19
10	D20	Chemicals	Chemical and chemical products	20
11	D21	Medical	Pharmaceuticals, medicinal chemical and botanical products	21
12	D22	Plastics	Rubber and plastics products	22
13	D23	Minerals	Other non-metallic mineral products	23
14	D24	Basic Metals	Basic metals	24
15	D25	Metal Products	Fabricated metal products	25
16	D26	Computer (office)	Computer, electronic and optical equipment	26
17	D27	Electrical	Electrical equipment	27
18	D28	Machinery n.e.c	Machinery and equipment, nec	28
19	D29	Auto	Motor vehicles, trailers and semi-trailers	29
20	D30	Other Transport	Other transport equipment	30
21	D31T33	Other	Manufacturing nec; repair and installation of machinery and equipment	31, 32, 33
22	D09	Mining support	Mining support service activities	09
23	D35	Electricity	Electricity, gas, steam and air conditioning supply	35
24	D36T39	Water	Water supply; sewerage, waste management and remediation activities	36, 37, 38, 39
25	D41T43	Construction	Construction	41, 42, 43
26	D45T47	Wholesale	Wholesale and retail trade; repair of motor vehicles	45, 46, 47
27	D49	Land Transport	Land transport and transport via pipelines	49
28	D50	Water Transport	Water transport	50
29	D51	Air Transport	Air transport	51
30	D52	Warehousing	Warehousing and support activities for transportation	52
31	D53	Post	Postal and courier activities	53
32	D55T56	Hotels	Accommodation and food service activities	55, 56
33	D58T60	Media	Publishing, audiovisual and broadcasting activities	58, 59, 60
34	D61	Telecom	Telecommunications	61
35	D62T63	IT Service	IT and other information services	62, 63
36	D64T66	Finance	Financial and insurance activities	64, 65, 66
37	D68	Real State	Real estate activities	68
38	D69T75	Profession	Professional, scientific and technical activities	69-75
39	D77T82	Administration	Administrative and support services	77-82
40	D84	Public	Public administration and defence; compulsory social security	84
41	D85	Education	Education	85
42	D86T88	Health	Human health and social work activities	86, 87, 88
43	D90T93	Arts	Arts, entertainment and recreation	90, 91, 92, 93
44	D94T96	Other Services	Other service activities	94,95, 96
45	D97T98	Private	Activities of households as employers;	97, 98

Table A4: Country List

Number	Country	Number	Country
1	Australia	23	Sweden
2	Austria	24	Switzerland
3	Belgium	25	Turkey
4	Canada	26	United Kingdom
5	Czech Republic	27	United States
6	Denmark	28	Argentina
7	Finland	29	Brazil
8	France	30	India
9	Germany	31	Indonesia
10	Greece	32	Hong Kong, China
11	Hungary	33	Malaysia
12	Ireland	34	Philippines
13	Israel	35	Russian Federation
14	Italy	36	Saudi Arabia
15	Japan	37	Singapore
16	Korea	38	South Africa
17	Luxembourg	39	Chinese Taipei
18	Mexico	40	Thailand
19	Netherlands	41	Viet Nam
20	Poland	42	Rest of the World
21	Portugal	43	China (ordinary)
22	Spain	44	China (processing)

Calibration

The income in the model is given by $I_n = w_n L_n + R_n + D_n = VA_n + R_n + (M_n - E_n)$. For China's processing production (denoted by CN2), $R_{CN2} = 0$ as there is no tariff revenue. Moreover, since all the imports, both goods and services, are used as intermediate inputs then exported after adding value, $E_{CN2} - M_{CN2} = VA_{CN2}$, and therefore $I_{CN2} = 0$, which implies there is no final consumption in $CN2$. This also implies that there will be no changes in real wages and real income for $CN2$ due to the changes in tariffs. However, when mapping the data into the model, M_{CN2} will be smaller than in reality. This is because there are only 24 aggregated service industries in the ICIO table, within which some services are tradable but others are not. As a result, when assuming all services are non-tradable, I_{CN2} will be negative. Furthermore, when all services are non-tradable, α^j_{CN2} will be zero for all tradable industries but will be positive for non-tradable industries. Specifically, for all tradable industries, $\alpha^j_{CN2} = (Y^j_{CN2} + D^j_{CN2} - \sum_{k=1}^{J} \gamma^{j,k}_{CN2} Y^k_{CN2})/I_{CN2} = (E^j_{CN2} + (M^j_{CN2} - E^j_{CN2}) - M^j_{CN2}))/I_{CN2} = 0$. This is because for $CN2$, all the outputs are being exported after processing, therefore $Y^j_{CN2} = E^j_{CN2}$. And because all the imports are being used as intermediate inputs, $\sum_{k=1}^{J} \gamma^{j,k}_{CN2} Y^k_{CN2} = M^j_{CN2}$ for all the tradable industries. However, for non-tradable industries, the numerator of α^j_{CN2} is negative. This is because while $CN2$ does not produce services, it has a positive expenditure on imported services in the ICIO table as services are being used as intermediate inputs in other tradable industries. Therefore, $\gamma^{j,k}_{CN2}$ are positive for non-tradable industries. Now if I assume that $M^j_{CN2} = 0$ for all service industries then $M^j_{CN2} \neq \sum_{k=1}^{J} \gamma^{j,k}_{CN2} Y^k_{CN2}$. As a result, $\alpha^j_{CN2} = (Y^j_{CN2} + D^j_{CN2} - \sum_{k=1}^{J} \gamma^{j,k}_{CN2} Y^k_{CN2})/I_n = (-\sum_{k=1}^{J} \gamma^{j,k}_{CN2} Y^k_{CN2})/I_{CN2} > 0$ for all non-tradable industries. This issue appears in China's processing production and applies to all the countries in my sample as well. However, for larger economies that have larger gross output in all non-tradable industries, the impact on calibration is relatively small.

Additional Results

Table A5: Welfare Effects of the 2018 Trade War

	Without Processing Trade		With Processing Trade	
	Real Wages	Real Income	Real Wages	Real Income
China (ordinary)	-0.13%	-0.18%	-0.09%	-0.10%
China (processing)	-	-	0.00%	10.2%
United States	-0.15%	0.03%	-0.15%	0.04%

Notes: Table A5 shows the real wages and real income effects of the 2018 trade war for China and the United States.

Table A6: Sectoral Contribution to Welfare Effects for China (Processing Production Only)

Industry	Contribution
Agriculture	-0.49%
Fishing	-0.02%
Mining (energy)	-0.21%
Mining (non-energy)	-0.06%
Food	0.46%
Textile	5.15%
Wood	-0.20%
Paper	0.36%
Petroleum	0.68%
Chemicals	0.54%
Medical	0.98%
Plastics	2.68%
Minerals	-0.02%
Basic Metals	-1.09%
Metal Products	0.66%
Computer (office)	55.76%
Electrical	15.06%
Machinery n.e.c	7.27%
Auto	1.22%
Other Transport	4.91%
Other	6.35%

Notes: Table A6 shows the sectoral contribution to the changes of real income for China's processing production as a result of the 2018-2019 trade war.

Table A7: Trade Effects of the 2018 Trade War for China

	With Processing Trade (Actual Regime)		Without Processing Trade (Counterfactual Regime)	
Industry	Imports	Exports	Imports	Exports
Agriculture	-12.16%	-1.39%	-17.18%	0.64%
Fishing	-7.37%	-30.62%	-11.74%	-37.43%
Mining (energy)	-1.61%	6.58%	-8.09%	6.92%
Mining (non-energy)	-5.78%	4.46%	-9.14%	8.80%
Food	-4.79%	-3.76%	-6.81%	-3.77%
Textile	-5.20%	-8.37%	-10.43%	-8.22%
Wood	-13.28%	-16.84%	-21.93%	-22.31%
Paper	-15.33%	-1.21%	-21.18%	-6.54%
Petroleum	-27.77%	63.18%	-44.85%	57.79%
Chemicals	-3.46%	-1.99%	-5.46%	-2.02%
Medical	-3.52%	12.42%	-9.80%	9.46%
Plastics	-1.73%	-3.49%	-3.74%	-4.61%
Minerals	-1.89%	-5.30%	-5.48%	-5.59%
Basic Metals	-2.34%	0.45%	-5.64%	0.51%
Metal Products	-3.97%	-7.31%	-9.95%	-7.53%
Computer (office)	-3.36%	-2.62%	-10.38%	-11.78%
Electrical	-3.59%	-2.19%	-13.35%	-7.19%
Machinery n.e.c	-1.80%	-4.12%	-2.93%	-4.74%
Auto	-3.30%	-10.92%	-4.09%	-11.32%
Other Transport	-1.15%	-0.99%	-1.65%	-1.28%
Other	-4.82%	-10.24%	-6.97%	-10.53%
Aggregate	-4.36%	-3.49%	-9.34%	-6.99%

Notes: Table A7 shows the trade effects of the 2018 trade war in China, computed as the percentage change in total imports and exports for each industry. Column 2-3 shows the estimates considering China's duty-free policy on processing imports; column 4-5 shows the estimates without considering this policy.

Table A8: Trade Effects of the 2018 Trade War for the United States

	With Processing Trade (Actual Regime)		Without Processing Trade (Counterfactual Regime)	
Industry	Imports	Exports	Imports	Exports
Agriculture	1.15%	-17.26%	1.61%	-18.44%
Fishing	0.72%	-6.52%	0.84%	-7.53%
Mining (energy)	0.06%	-8.51%	0.27%	-9.00%
Mining (non-energy)	7.96%	-22.75%	8.95%	-23.34%
Food	-5.33%	-9.80%	-5.14%	-10.13%
Textile	-9.25%	-15.86%	-8.97%	-15.45%
Wood	-7.85%	-28.75%	-7.37%	-29.74%
Paper	1.67%	-23.58%	2.27%	-24.14%
Petroleum	33.58%	-23.71%	36.58%	-24.99%
Chemicals	-3.09%	-5.92%	-2.96%	-6.00%
Medical	4.21%	-5.54%	4.27%	-5.79%
Plastics	-5.59%	-1.74%	-5.53%	-1.82%
Minerals	-12.57%	-8.44%	-12.30%	-8.92%
Basic Metals	-19.16%	-18.20%	-19.02%	-18.27%
Metal Products	-16.52%	-13.66%	-16.14%	-14.12%
Computer (office)	-14.91%	-18.56%	-16.07%	-16.11%
Electrical	-19.10%	-21.44%	-19.16%	-20.69%
Machinery n.e.c	-5.23%	-2.39%	-5.18%	-2.43%
Auto	0.26%	-1.82%	0.35%	-1.89%
Other Transport	-1.45%	-0.68%	-1.38%	-0.67%
Other	-7.99%	-5.75%	-7.90%	-5.93%
Aggregate	-5.41%	-9.94%	-5.40%	-9.92%

Notes: Table A8 shows the trade effects of the 2018 trade war in the United States, computed as the percentage change in total imports and total exports for each industry. Column 2-3 shows the estimates considering China's duty-free policy on processing imports; column 4-5 shows the estimates without considering this policy.