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Keywords: Global value chains, US–China trade war, Trump tariffs

JEL classification: F15; F53

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Abstract

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1. Introduction

Global value chains (GVCs), the cross-border splitting of the production process within vertically integrated manufacturing industries, have been a key facet of economic globalization over the past several decades, especially in East Asia (Athukorala and Yamashita, 2006; Baldwin, 2008; Baldwin and Lopez-Gonzalez, 2015; Pomfret and Sourdin, 2018; Femandes et al., 2021). With the cross-border fragmentation of products within GVCs, a participating country focuses on some specific segments where it has comparative advantages, instead of mastering the entire production process. Accordingly, GVC participation has come to be the new way of thinking about development in emerging economies (World Bank, 2020).

The system of GVCs has, however, recently been hit by a series of large-scale shocks, including the global financial crisis (Eaton et al., 2016), the Great East Earthquake in Japan (Todo et al., 2015; Boehm et al., 2019), flooding in Thailand (Hayakawa et al., 2015), and the Covid-19 pandemic (Friedt and Zhang, 2020; Kejzar and Velic, 2020; Hayakawa and Mukunoki, 2021; Meier and Pinto, 2020). These studies have led to further understanding of the risks and resiliency of GVCs to shocks.¹ As economic linkages among countries are becoming stronger through the development of GVCs, how GVCs react to negative shocks has emerged as a key research topic.

Our paper adds new evidence to this line of research by examining the short-run effects of a large-scale shock on GVCs, namely, the US–China trade war. Whereas the findings of the aforementioned studies are mainly drawn from episodes of massive disruptions on the supply side of GVCs (e.g., flooding on factory floors), our focus is on the impact of demand side shocks on GVCs. More specifically, focusing on machinery industries, we examine how variations in US imports from China were passed onto three economies, namely, Japan, South Korea, and Taiwan (collectively, JKT below) that supply intermediate inputs to China, mediated by the input-output linkages between JKT and China. Indeed, JKT has comprised the top three exporters to China in machinery industries, accounting for 50%. We empirically examine the effect of China’s exports of finished machinery goods to the US on JKT’s exports of machinery parts to China.

An empirical challenge in this context is simultaneity bias: China’s exports to the US and China’s input imports from JKT are simultaneously determined. To overcome this bias, we take advantage of an abrupt policy change under the Trump administration in the

¹ Eaton et al. (2016) reported that GVCs were the reason for the 20 percent fall of global trade relative to global GDP during the global financial crisis in 2008. U.S. firms that relied on Japanese inputs experienced a large drop in production after the Great East Japan Earthquake in 2011. Hayakawa et al. (2015) also found that small affiliates of Japanese multinational firms in flooded regions of Thailand in 2011 lowered the share of local inputs (i.e., inputs in the local economy in Thailand), disrupting GVCs. More recently, the short-run negative effect of the COVID-19 pandemic on input supplier countries on GVCs has been shown in several studies (e.g., Hayakawa and Mukunoki, 2021), while others argue that such disruptions have short-lived effects (Antras, 2020; Yamashita and Fukasaku, 2021).

US–China trade war. The changes in US tariffs on Chinese goods in 2018/2019 had a direct effect on China’s exports to the US, but not on China’s input imports from supplier countries. Thus, US tariffs on Chinese goods provide a valid instrument for input imports to China. By applying this instrumental variable approach, we identify the ripple effects of the US demand shock induced by the US–China trade war on the three input suppliers.

We find that a change in US import demand from China indeed generated negative ripple effects, which were transmitted to input-supplying economies: A decrease in China’s exports to the US caused by the Trump tariffs led to the decrease in China’s input imports from JKT. However, these negative effects were not uniform across JKT. When examining each of the supplying economies, we found that Taiwan was hit the hardest by a drop in US demand for Chinese goods. We provide evidence suggesting that this was partly driven by the way that multinational enterprises (MNEs) in Taiwan set up their export platforms in China, amplifying the adverse demand shocks.

This study is related to the strand of literature estimating the effects of the Trump tariffs on trade: The evidence so far is concentrated on the direct effects of tariffs on the US economy, including the pass-through to consumer prices (Amiti et al., 2019; Amiti et al., 2020; Fajgelbaum et al., 2020; Flaaen et al., 2020), the price effects on retailers (Cavallo et al., 2021), the effects on US exporters dependent on foreign inputs (Handley et al., 2020), the impact on the stock market (Egger and Zhu, 2020), and the effects on political sentiments (Blanchard et al., 2019). Although these works investigated the direct tariff effects, our focus is to examine indirect or spillover effects of tariff-driven negative shocks on GVCs.

Some prior work has considered the effects on other countries of the US–China tariffs: Mao and Gorg (2020) computed the cumulative tariff rates on third countries connected by GVCs as a result of the US tariff hikes. They argued that US imports from China are likely to be used as intermediates in goods that are then exported again by the US, so an increase in the tariff on imports from China affects third countries by increasing the prices, especially for countries that are deeply integrated with US production through GVCs. Ma et al. (2021) investigated the effects of retaliatory tariffs imposed by China on China’s imports from the US.² Cigna et al. (2021) confirmed the negative effect of US tariffs on US imports from China, but more importantly, reported the absence of short-term trade diversion effects toward third countries following the Trump tariffs. A more comprehensive analysis of trade diversion effects in global trade was undertaken by Fajgelbaum et al. (2020), and they found heterogeneous responses by third countries with an increase of global trade in the tariff-targeted products in the US–China trade war.

Differentiating our work from the above studies, the present study takes a unique approach in which we specifically examine the negative *downstream* demand shocks on the *upstream input suppliers* to China, whose exports were subject to the Trump tariffs. A novel feature of our study is the use of the abrupt change in US trade policy as an instrument

² Chor and Li (2021) showed a negative effect of US tariffs on night-time luminosity in China, while Cui and Li (2021) found a negative effect on Chinese new firm entry rates.

for demand shocks, which are then propagated through GVCs to upstream countries. Furthermore, as documented by several studies (e.g., Fajgelbaum et al., 2020), the effects of the US–China tariffs were found to be heterogeneous. We attribute this to the strength of the input-output linkages with China.

2. Shocks to Global Value Chains

GVCs are broadly described as the process of breaking up vertically integrated production processes into finer stages and relocating each stage to the most suitable locality across borders (World Bank, 2020). Naturally, GVCs cover cross-border exchanges of parts and components in intra-firm transactions between MNEs and their foreign affiliates, together with international arm’s-length subcontracting transactions (inter-firm trade with unaffiliated suppliers) in the extended networks.

By this definition, GVCs are susceptible to amplifying a shock to the system. For instance, Yi (2003) argues that even a small tariff reduction has a so-called “magnification effect” on fragmentation trade, as empirically demonstrated in Hayakawa and Mukunoki (2022). This effect arises because, unlike finished products, components and unfinished products can cross international borders multiple times before reaching the final stage of the production process. Any marginal reduction in the protection scheme can significantly lower trade costs. On the other hand, Antràs (2020) argues that the existence of relationship stickiness in GVCs remains resilient against short-term external shocks. Because GVC networks depend heavily on technology-intensive components (e.g., speaker systems, memory chips, microprocessors, power and mechanical components, or advanced design and development) supplied from related main suppliers, this procurement arrangement essentially blocks outside vendors from becoming involved with GVCs, especially in short-term shocks.³

The advantages of GVCs include adaption to volatile markets, as suppliers can respond quickly to changing market conditions by allowing for the replacement of workers and suppliers on short notice. In a study of the effects of the Great East Japan Earthquake in 2011, Todo et al. (2015) present evidence that more extensive pre-existing production networks in terms of the number of suppliers outside the affected regions are associated with quicker resumption of production and faster recovery of supplier links. A disadvantage, however, is that such networks can build up excessively relation-specific

³ The other form of GVC network is based on a modular production network (Sturgeon, 2003). This form is normally driven by contract manufacturers who provide traditional and standardized manufacturing functions, product (re)design, component processing and purchasing, inventory management, and routine tests, as well as aftersales services and repairs. It is also facilitated by highly standardized inter-firm linkages requiring less frequent and intense interactions. In regard to shocks, GVC networks with modularity built in may also work toward a swift recovery from a supply disruption due to the lower costs of switching input suppliers.

investments and inefficient bilateral dependency between downstream firms and suppliers. In sum, there is a strong need to examine this further channel for how shocks to GVCs are transmitted among the countries involved.

We focus our analysis on an episode of the US–China trade war between 2018 and 2019.⁴ Former US President Trump launched a trade war against China immediately after taking office by imposing scheduled tariffs, beginning with a tariff of 30% on imports of solar panels, a 20% increase in tariffs on washing machines (Flaaen et al., 2020), a 25% increase in tariffs on steel, and a tariff of 10% on aluminum. Although China was not explicitly named in the initial wave of tariffs, it was obvious that China was targeted because it was the major exporting country of the above products to the US. Subsequently, the US government specified China as a target once the tariff rates are changed. In 2018–2019, the Trump administration implemented five rounds of changes in tariffs, occurring in July, August, and September in 2018 and June and September in 2019, with the aim of hitting imports from China. Ultimately, the tariff changes corresponded to about 2.6% of US GDP, with the average tariff rate peaking at 25.8%, which was up from 3.7% (Fajgelbaum and Khandelwal, 2022). This amounts to around 17.6% of total US imports in 2017, and two-thirds of the 10-digit product lines (Fajgelbaum and Khandelwal, 2022).

3. Empirical Strategy

This section explains our empirical framework to investigate how Chinese imports of inputs from JKT are affected by changes in Chinese exports to the US, driven by the imposition of the Trump tariffs. After presenting our estimation equation and strategy, we give an overview of our data.

3.1. Specification

In our empirical analysis, we focus on trade in four machinery industries—general machinery (HS 84), electrical machinery (HS 85), transport equipment (HS 86, 87, 88, and 89), and precision machinery (HS 90, 91, and 92)—for the following reasons. First, trade data allow us to separate final goods and intermediate goods even at the granular level of the commodity classification under the HS system. For example, HS 8708 includes parts and accessories for the motor vehicles of headings 8701 to 8705. More importantly, monthly trade data, which have a more suitable time window for examining the disruption to GVCs in the short run, are available. In contrast, alternative measures of GVCs, such as trade in value-added, provide only annual values. Second, machinery industries, as shown later, account for a dominant share of total exports from JKT to China. At the same time, these

⁴ For a fuller description and chronology of the US–China trade war, see Section 3 of Egger and Zhu (2020), as well as Bown (2021) and Fajgelbaum and Khandelwal (2022).

were the main product lines targeted by the Trump tariffs. Considering all these elements, our focus on machinery industries is justified in this study.

The main estimation equation is as follows:

$$\ln Parts_{cpt} = \beta \ln CHN \text{ exports to USA}_{i(p \in i)t} + \gamma \ln(1 + China \text{ Tariff}_{cpt}) + u_{cp} + u_{ct} + \epsilon_{cpt}. \quad (1)$$

Here, $Parts_{cpt}$ is exports of machinery part p (defined at the HS 2017 eight-digit level) from country c in JKT (Japan, South Korea, or Taiwan) to China at time t (months) during the period January 2018 to December 2019. $CHN \text{ exports to USA}_{it}$ refers to China's exports of finished products in machinery industry i to the US at time t . Industry i is the one to which machinery part p belongs. $China \text{ Tariff}_{cpt}$ is the tariff rate imposed on product p imported from country c to China at time t . If the rate was, for example, 5%, it takes a value of 0.05. β and γ are coefficients to be estimated. We expect positive and negative signs for these coefficients, respectively. A negative value of β indicates that a decrease in China's exports of finished machinery products to the US results in a decrease in China's imports of machinery parts from JKT.

Variables u_{cp} and u_{ct} are country-product and country-time fixed effects, respectively. The former is used to control for time-invariant country-product characteristics, such as the distribution of firm productivity in the exporting countries or the technology and factor intensity at a country-product level. This type of fixed effect may also control for differences in the share of exports out of total sales across products in China (i.e., export penetration into China). The country-time fixed effects control mainly for factor prices (e.g., wages) in exporting countries. Unobservable macro shocks (e.g., changes in China's macroeconomic conditions) are also absorbed by the country-time fixed effect. ϵ_{cpt} is an error term.

Endogeneity bias is concern in Equation (1): our main independent variable is associated with the size of demand for inputs in China (used for exports to the US), whereas our dependent variable is exports of those inputs to China. Thus, this supply-demand nexus may yield a simultaneity issue. Although we control for several fixed effects, there are unobservable elements that are not controlled for by these fixed effects and that affect both the supply and demand of inputs. For example, deregulations in foreign direct investment in some industries in China may encourage the entry of both output producers and input suppliers into China. Thus, an increase in output producers in China raises both the volume of exports and the demand of inputs, whereas an increase in input suppliers results in decreasing input imports. If the latter effect dominates the former, then deregulations would increase output exports but decreases input imports. In this case, when we estimate Equation (1) by the ordinary least square (OLS) method, the error term will be negatively correlated to our main independent variable. As a result, the estimate of β by OLS suffers

from downward bias.

To tackle this endogeneity issue, we employ the instrumental variable (IV) method. Specifically, we use the weighted average of US tariffs levied on finished machinery products imported from China as an instrument for US demand. China's exports to the US (defined at the HS six-digit level) in 2017 (pre-trade war period) are used as a weight to compute the weighted average tariff for each machinery industry. This IV is reasonable: as found in Amiti et al. (2019) and Flaaen et al. (2020), an increase in US tariffs is expected to decrease China's exports of final products to the US. In short, US tariffs against China will be associated with a change in China's exports of finished machinery products to the US. Furthermore, the imposition of US tariffs on imports from China was not intended to limit input exports from JKT to China and thus will not be directly associated with those exports. Thus, US tariffs against China will satisfy the exclusion restriction in the import demand function described in Equation (1).

3.2. Data Issues

The examined products in our study are defined at the eight-digit level in China's HS 2017 classification. Referring to the list of the commodities labeled as "parts and components" and "final goods" in machinery industries at the 6-digit level of the HS classification, as provided by Kimura and Obashi (2010), we classify products at the eight-digit level into either finished goods or parts.⁵ As specified in Equation (1), we focus on the intra-industry input-output relationship by focusing on four machinery industries. For example, although semiconductors (categorized in the electrical machinery industry) are used in producing both electrical machinery and transport equipment products (e.g., passenger cars), we do not consider the use of semiconductors in the transport equipment industry as inputs.⁶

Data on trade values (i.e., $Parts_{cpt}$ and $CHN\ exports\ to\ USA_{it}$) are obtained from the Global Trade Atlas (IHS Markit). The US tariffs against China (i.e., our instrumental variable) are constructed by using World Integrated Trade Solution (WITS) data and the replication files of Fajgelbaum et al. (2020) for the specific US tariffs. Since this variable does not change across JKT, our identification comes from the differences across industries (4 industries) and times (24 months). WITS data are also used for Chinese tariffs applied to

⁵ We did not use the Broad Economic Categories (BEC), which classify products into either capital goods, consumption goods, or intermediate goods (or not classified elsewhere). Machinery parts identified in Kimura and Obashi (2010) include 14% of capital goods (e.g., electrical capacitors, fixed, variable or adjustable [HS 8532]), 10% of consumption goods (e.g., connectors for optical fibers, optical fiber bundles or cables [HS 853670]), and 96% of intermediate goods in the BEC. The list in Kimura and Obashi (2010) includes not only intermediate goods but also other types of machinery goods as parts that are traded in the business-to-business market.

⁶ Another issue is that since the list in Kimura and Obashi (2010) includes only parts and components categorized in HS 84 to HS 92, we do not consider intermediate products categorized in other chapters (e.g., tires in HS 401120).

China's imports from JKT. Note that this tariff variable is different across not only industries and times but also the three economies because South Korea and Taiwan have preferential trade agreements (e.g., free trade agreements) with China. We use the lowest available tariff rates for exports from each economy to China.

Before reporting our estimation results, we give an overview of trade values for the studied economies. The upper-left panel of Table 1 shows the top five HS two-digit codes in terms of export values from China to the US in 2018. The largest one is the electrical machinery industry (HS 85), followed by the general machinery industry (HS 84). The sum of exports in these two industries accounts for almost 50% of total exports from China to the US. Figure 1 also shows the temporal trend of monthly exports from China to the US between January 2018 and December 2019 for the top three HS goods in Table 1, together with the simple average of US tariffs against goods from China. The monthly exports are normalized to a value of 1 for January 2018. We can see that the exports in the three industries started a sharp decline from the fourth quarter of 2018. Those exports slightly recovered in the first half of 2019 but declined again thereafter.

< **Table 1 & Figure 1** about here >

The remainder of Table 1 shows the figures for exports from JKT to China in 2018. In all three JKT economies, the electrical machinery industry is dominant. In South Korea and Taiwan, exports in this industry account for around or greater than 50% of total exports to China. In Japan, the general machinery industry also has a relatively high share, at 23%. The general machinery industry is also ranked second in South Korea and is ranked third in Taiwan. Thus, as in the case of China's exports to the US, the general and electrical machinery industries are the main industries of the exports from JKT to China.

Next, we take a closer look at the machinery trade. Figure 2 shows the monthly exports of machinery parts from JKT to China and those of finished machinery products from China to the US. Here, too, these exports are normalized to a value of 1 for January 2018. We also present the simple average of US tariff rates on finished machinery products from China. Exports of finished machinery products from China started to decline around the end of 2018, and 2 months later those of machinery parts from JKT decreased. These two kinds of exports seem to change in tandem. Figure 2 also shows a large increase of US tariffs on finished machinery products from China in July 2018. On average, they rise by more than 10 percentage points.

< **Figure 2** about here >

4. Estimation Results

This section presents our estimation results. Table 2 reports the basic statistics for our variables. We first pool China's imports of inputs from JKT and estimate how these imports are influenced by a change in US imports of outputs from China. Table 3 presents various estimation results with product-clustered standard errors. The coefficient for China's exports to the US in column (I) by OLS is significantly positive, as expected. Specifically, it indicates that a 1% decrease in China's exports of finished machinery products to the US is associated with a 0.088% decrease in exports of machinery parts from JKT to China. The estimated coefficient for China's tariffs is not significant.

< **Tables 2 & 3** about here >

In the OLS estimation, observations with zero-valued trade are automatically dropped because we take the logarithm of the dependent variable. However, as Melitz (2003) suggested, trade values can be systematically zero, suggesting that dropping zeros leads to the elimination of potentially useful information, resulting in sample selection bias. To address this issue, we used the Poisson pseudo maximum likelihood (PPML) method, which enables us to naturally incorporate zero-valued trade (Silva and Tenreyro, 2006) in column (II). The coefficient for China's exports to the US continues to be significantly negative. Its absolute magnitude rises slightly compared with the result obtained using the OLS method.

Column (III) in Table 3 reports the estimation results by the IV method, which drops observations with zero-valued trade but allows for interpretation of causality. The test statistics for diagnosing under-identification (Kleibergen-Paap rk *LM* statistic) and weak identification (Kleibergen-Paap rk Wald *F* statistic) show reasonably high values: The high value in the former test indicates that the rank condition is satisfied and that the equations are identified; the high value in the latter test suggests that our IV estimates are unlikely to suffer from weak instrument bias. The estimated coefficient for China's exports to the US is again significantly positive. Notably, the magnitude of the coefficient rises greatly compared with the results produced by the OLS and PPML methods. A 1% decrease in China's exports to the US results in a 0.4% decrease in China's imports of imports from JKT. This magnitude is economically large. This increase in the coefficient also implies that our OLS estimate in column (I) suffers from downward bias.

Next, we control for additional trade restraints imposed by the US on China other than tariffs. The US government has also imposed export controls on US firms exporting to China: In May and August 2019, it added Huawei and its affiliates to the Entity List, which is the official catalog of foreign companies to which it is illegal for US entities to provide goods or services without a government-designated license (Bown, 2020). This control aimed to prevent Huawei from getting semiconductors for 5G equipment from the US. Such negative shocks to a huge company such as Huawei would also presumably be damaging to the businesses of many non-Entity List companies in China. Consequently, the negative impacts may appear in JKT's exports to China. However, this blacklisting may also generate

trade diversion that Huawei and other Chinese firms could respond to, for example, switching the purchase of semiconductors from the US to South Korea (e.g., Samsung Electronics) or Taiwan (e.g., TSMC). In short, not only tariffs but also export controls may have significant effects on exports from JKT to China.

We try to capture some of the possible effects of export controls by introducing a dummy variable that takes a value of 1 for exports of machinery parts in the electronic industry after July 2019.⁷ This dummy variable (*Export control*) is motivated by the fact that most of the imports from the US by Huawei belong to the electronic industry.⁸ The results are shown in Table 4. Coefficients for China's exports to the US and China's tariffs do not change much, but the former has an insignificant coefficient in the PPML method. The coefficients for the export control dummy are significantly negative in the OLS and IV methods, indicating that the negative effects are larger than the positive effects. Specifically, the IV result shows that exports of electrical machinery parts to China decreased by 13% ($= \exp(-0.138)-1$) after July 2019.

< **Table 4** about here >

Table 5 splits the sample by economy (Japan, South Korea, and Taiwan). In this estimation, we control for product fixed effects and time fixed effects, instead of country-product fixed effects and country-time fixed effects. Interestingly, while the coefficients on China's exports to the US are all positive in each column, the key variable shows a statistically significant effect for only Taiwan, as shown in column (III): A 1% decrease in China's exports to the US results in a 0.8% decrease in Taiwan's exports to China, which is greater than the average effect in the IV results of Table 3. Also, the export control dummy has a significantly negative coefficient for only Taiwan. In sum, our results suggest that the trade war between the US and China had the largest adverse effects on Taiwan among the JKT economies in terms of both tariffs and export controls.

< **Table 5** about here >

5. Discussion

In this section, we discuss a possible mechanism underpinning the highlighted heterogeneous effects of change in US demand across JKT. The main finding in the

⁷ Until mid-August, trade with Huawei and its affiliates was allowed under a temporary general license. Thus, we create a dummy variable based on the official announcement in August. Note that conducting a well-established analysis of this issue is challenging and beyond our scope in this paper since it requires the data on firms' importing behaviors.

⁸ The products Huawei purchased from US suppliers are mainly processor chips and other technologies which are used to produce 5G devices, such as smartphones.

preceding section is that China's import of inputs is sensitive to changes in US demand for final goods. However, we also found that the sensitivity is driven primarily by Taiwan and less so by Japan and South Korea.

We conjecture that these heterogeneous differences are driven by differences in the way MNEs from the different JKT economies have set up export platforms in China. Specifically, the main role of Japanese and South Korean MNEs in China is not to export their assembled products to the US. Instead, their MNE operations predominantly focus on serving the market in China. On the other hand, Taiwanese MNEs more frequently use their production bases in China as an export platform to the US. To facilitate the operations, Taiwanese MNEs also import machinery parts from Taiwan. Thus, Taiwan is most likely to be affected by the trade tension between China and the US. Below, we provide two main pieces of evidence to support this claim.

First, we start by presenting evidence that covers the JKT economies. We examine the share of exports from China to the US in total sales at the firm level. Specifically, we examine how this share is associated with the shares of imports from the JKT economies in total imports. The firm-level data on total sales are obtained from a manufacturing survey conducted by China's National Bureau of Statistics. The firm-level export and import data were provided by China Customs. We use these data for 2013. Specifically, we estimate the following equation:

$$\frac{\text{Exports to USA}_f}{\text{Total sales}_f} = \delta_1 \text{Import share from JPN}_f + \delta_2 \text{Import share from KOR}_f + \delta_3 \text{Import share from TWN}_f + u_s + \epsilon_f \quad (2)$$

Subscript f indicates a firm. We control for sector fixed effects, which are defined at the four-digit level in the industrial classification of the manufacturing survey. We estimate this Equation (2) by the OLS method.

Table 6 presents various estimation results. In columns (I) and (II), we include firms in all manufacturing industries. Only firms in machinery industries are examined in columns (III) and (IV). "Drop if export share > 1" indicates whether we drop firms where the share of total exports in total sales exceeds a value of 1. Due to our mixing of different data sources (i.e., customs and a manufacturing survey), some firms show total exports greater than total sales. The results indicate that firms with a higher share of imports from Japan are the least likely to export to the US, followed by those with a higher share of imports from South Korea. In contrast, the coefficients for the import share from Taiwan are significantly positive or not significant. Firms with a higher share of imports from Taiwan tend to export more to the US than those with a higher share of imports from Japan or South Korea. Thus, the trade tension between China and the US is likely to affect firms importing from Taiwan most strongly.

< Table 6 about here >

Second, we present some secondary evidence to support our main findings. For Japan, we examine the sales and procurement sources in Japanese machinery MNEs in China. Data are taken from the Basic Survey of Japanese Business Structure and Activities for 2019 conducted by the Ministry of Economy, Trade and Industry, Japan. This survey shows that Japanese MNEs in China do not export their goods to the US. The share of exports to North America (including the US) in total sales accounts for less than 1%. The domestic Chinese market is their main target, accounting for 48%. Correspondingly, 16% of the total sales are destined to Japan.⁹ Due to this sales structure, Japanese MNEs in China are less prone to have their operations directly affected by the trade war. Nevertheless, some local Chinese firms to which Japanese MNEs sell their goods may export to the US. In short, although the trade war could affect Japan's exports to China through ripple effects, the net impacts would be smaller, which is seen in Table 5.

A similar account can be seen for South Korean MNEs. Lovely et al. (2021), for example, show that South Korea benefitted from the trade war owing to US import shifts from China to South Korea in some sectors. However, they also raise the possibility that reduced US imports from China may hurt China's demand for South Korean exports because South Korean machinery and intermediates are embedded in Chinese production, some of which flow to the US. However, our results show that the US–China trade war did not significantly reduce South Korea's exports to China. To understand the results in Table 5 from the perspective of South Korean MNEs, we focus on their motives for entry into China and also their diversification in GVCs beyond China. Major South Korean MNEs such as Samsung Electronics and Hyundai Motor have targeted the Chinese domestic market, rather than pursuing other markets like the US, by seeking efficiency (lowering costs). For example, Samsung Electronics and Hyundai Motor started to reshape their value chains by shifting production from China to Vietnam and India even before the trade war, because of not only rising labor costs but also decreasing domestic sales in China.¹⁰ Thus, this hints that the trade war less likely affected South Korean MNEs in China.

The estimation result for Taiwan that differentiates it from Japan and South Korea is also related to MNE operations. Taiwan has had a huge increase in outward FDI to China since the early 2000s concentrated in the electronics and machinery industries, where export-platform FDI was implemented (Yang et al., 2010), and this has contributed a large share of China's exports (Tung and Hung, 2012). This development facilitated intra-industry trade between Taiwan and China (Zhang, 2005), resulting in China becoming Taiwan's

⁹ Japanese MNEs in China in the machinery industries use some inputs imported from Japan, with 30% of their total inputs from Japan and 60% from China.

¹⁰ For example, Samsung Electronics began to withdraw smartphone production plants in Shenzhen and Tianjin in 2018, and also stopped operations in October 2019 at its Huizhou plant in Guangdong Province, the last smartphone production base in China. It has relocated the smartphone factories sequentially to Vietnam and India (<https://www.reuters.com/article/us-samsung-elec-china-idUSKBN1WH0LR>).

largest export destination since 2005. According to statistics from the Ministry of Economic Affairs of Taiwan, the ratio of overseas production for Taiwan's export orders reached 91% in information, communication, and technology products and 75% in machinery industries for 2019-2020. Their overseas production base is concentrated in China, implying a positive relationship between China's exports of final goods to the US and Taiwan's exports of intermediates to China. China's exports of electronics and machinery products to the US decreased sharply owing to the China-US trade war, thereby affecting Taiwan's exports to both US and China. Taiwan is one of China's main intermediates suppliers (19% in 2019), and also contributes a high proportion of intermediates (16%) in GVCs that involve China (MAC, 2021). Thus, among JKT, Taiwan suffered the most from a significant decrease in machinery exports to China along with the decrease in China's exports to the US during this trade war.

6. Conclusion

This study investigated how changes in US imports from China altered China's intermediate imports in machinery industries from Japan, South Korea, and Taiwan, linked by GVCs. To address the simultaneity bias in this input-output linkage, we used the Trump tariffs as an instrument for changes in downstream demand. We found that negative ripple effects of the tariffs were propagated via GVCs, reducing China's imports of inputs from supplier countries. However, these effects were heterogeneous: Taiwan was hit the hardest among the three economies. This difference seems to be related to the strategy of Taiwanese MNEs to predominantly set up export platforms in China, amplifying the effects of tariff increases from the US. In short, the effect of shocks on the input trade differed depending on how those inputs were linked with GVCs. The input suppliers more closely linked with the whole chain suffered greater damage even when negative shocks hit the chain where they were not directly involved.

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Table 1. Overview of Trade Values in 2018 (Billion USD, %)

Rank	HS	Value	Share	HS	Value	Share
From CHN to USA				From JPN to CHN		
1	85	119	25	85	44	25
2	84	103	22	84	41	23
3	94	33	7	87	18	10
4	95	19	4	90	16	9
5	39	18	4	39	10	5
From KOR to CHN				From TWN to CHN		
1	85	100	49	85	113	64
2	84	24	12	90	15	8
3	90	15	7	84	15	8
4	29	14	7	39	10	5
5	39	12	6	29	7	4

Source: Global Trade Atlas

Note: CHN = China, JPN = Japan, KOR = South Korea, and TWN = Taiwan.

HS 29 = Organic chemicals, HS 39 = plastics, HS 84 = nuclear reactors, boilers, machinery, and mechanical applications, parts; HS 85 = electrical machinery and equipment, HS 94 = furniture, HS 95 = toys.

Table 2. Basic Statistics

	Obs	Mean	Std. Dev.	Min	Max
ln Parts	43,830	12.588	3.143	0	22.633
ln (CHN exports to USA)	43,830	21.981	0.976	19.696	23.125
ln (1 + CHN tariffs)	43,830	0.049	0.042	0	0.300
ln (1 + USA tariffs)	43,830	0.065	0.056	0.001	0.220

Source: Authors' compilation.

Table 3. Baseline Results

Method	(I) OLS	(II) PPML	(III) IV
ln (CHN exports to USA)	0.088* [0.048]	0.135** [0.067]	0.405** [0.165]
ln (1 + CHN tariffs)	-0.522 [0.717]	0.944 [1.687]	-1.012 [0.747]
First-stage regression			
ln (1 + USA tariffs)			-2.275*** [0.052]
Number of observations	43,830	53,928	43,830
Adjusted/Pseudo R-squared	0.9070	0.9900	
Underidentification test			116.9
Weak identification test			1946.8

Notes: This table reports the estimation results obtained using the OLS, PPML, and IV methods. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by products. In all specifications, we control for country-product and country-time fixed effects. The Kleibergen-Paap rk *LM* statistic and the Kleibergen-Paap rk Wald *F* statistic are used for under-identification and weak identification tests, respectively.

Table 4. Robustness Checks: Export Control Measures

Method	(I) OLS	(II) PPML	(III) IV
ln (CHN exports to USA)	0.131** [0.053]	0.07 [0.062]	0.382** [0.157]
ln (1 + CHN tariffs)	-0.538 [0.715]	0.811 [1.674]	-0.866 [0.729]
Export control	-0.063* [0.036]	0.085 [0.091]	-0.138** [0.057]
First-stage regression			
ln (1 + USA tariffs)			-2.390*** [0.037]
Number of observations	43,830	53,928	43,830
Adjusted/Pseudo R-squared	0.9070	0.9910	
Underidentification test			142.0
Weak identification test			4215.6

Notes: This table reports the estimation results obtained using the OLS, PPML, and IV methods. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by products. In all specifications, we control for country-product and country-time fixed effects. The Kleibergen-Paap rk *LM* statistic and the Kleibergen-Paap rk Wald *F* statistic are used for under-identification and weak identification tests, respectively.

Table 5. Estimation Results by Exporting Country

	(I)	(II)	(III)
	JPN	KOR	TWN
ln (CHN exports to USA)	0.299	0.142	0.790***
	[0.271]	[0.308]	[0.250]
ln (1 + CHN tariffs)	-0.257	-4.013	-0.311
	[0.853]	[3.093]	[1.679]
Export control	-0.117	-0.124	-0.184**
	[0.089]	[0.115]	[0.093]
First-stage regression			
ln (1 + USA tariffs)	-2.364***	-2.340***	-2.412***
	[0.043]	[0.048]	[0.043]
Number of observations	16,493	13,668	13,669
Underidentification test	156.2	114.5	101.8
Weak identification test	2999.5	2329.3	3153.7

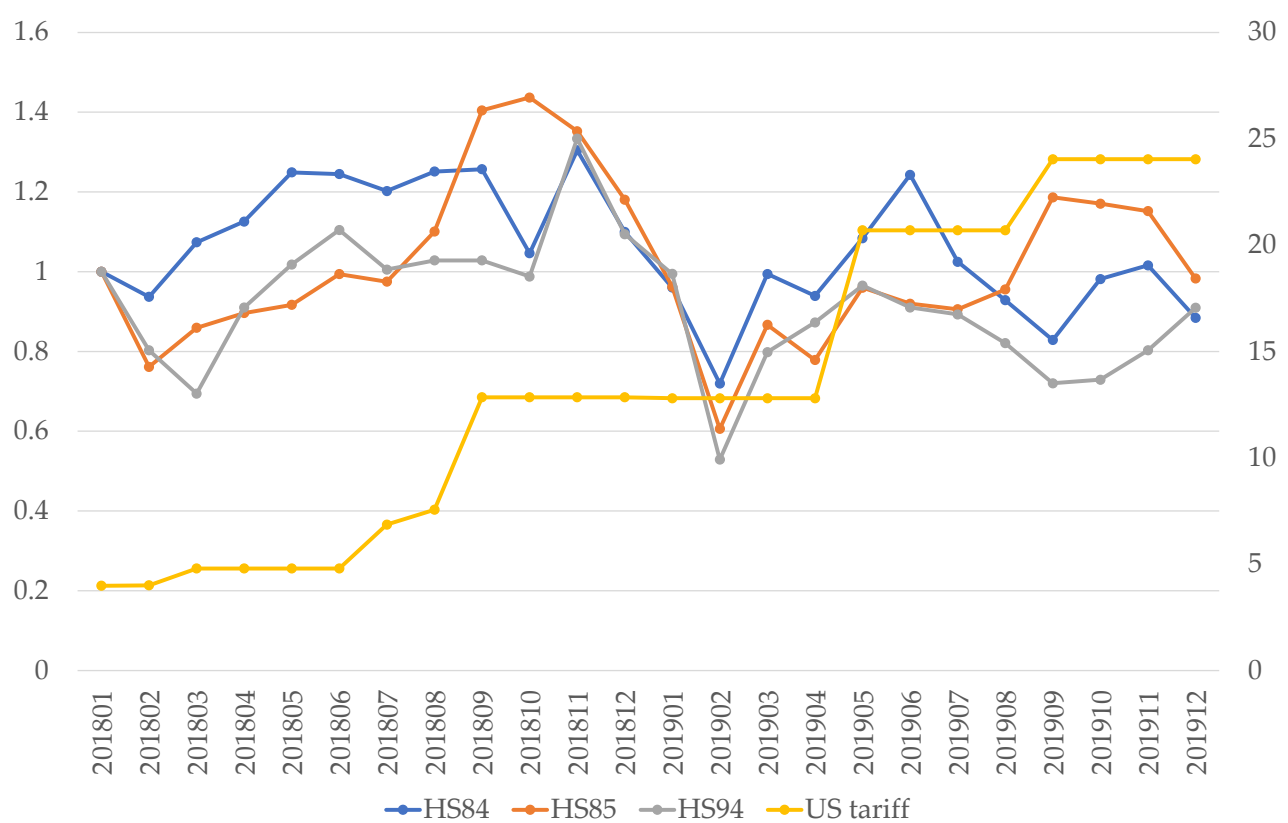
Notes: This table reports the estimation results obtained using the IV method. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively. The standard errors reported in parentheses are those clustered by products. In all specifications, we control for product fixed effects and time fixed effects. The Kleibergen-Paap rk *LM* statistic and the Kleibergen-Paap rk Wald *F* statistic are used for under-identification and weak identification tests, respectively.

Table 6. Firm-level Regression of the Share of Exports to the US in Total Sales

	(I)	(II)	(III)	(IV)
Import share from JPN	-0.103*** [0.005]	-0.037*** [0.002]	-0.090*** [0.008]	-0.033*** [0.002]
Import share from KOR	-0.051*** [0.007]	-0.023*** [0.002]	-0.076*** [0.008]	-0.032*** [0.003]
Import share from TWN	0.032* [0.017]	0.004 [0.003]	0.018 [0.036]	-0.006 [0.004]
Industries	All	All	Machinery	Machinery
Drop if export share > 1		Yes		Yes
Number of observations	41,947	35,955	17,293	15,016
Adjusted R-squared	0.034	0.102	0.005	0.059

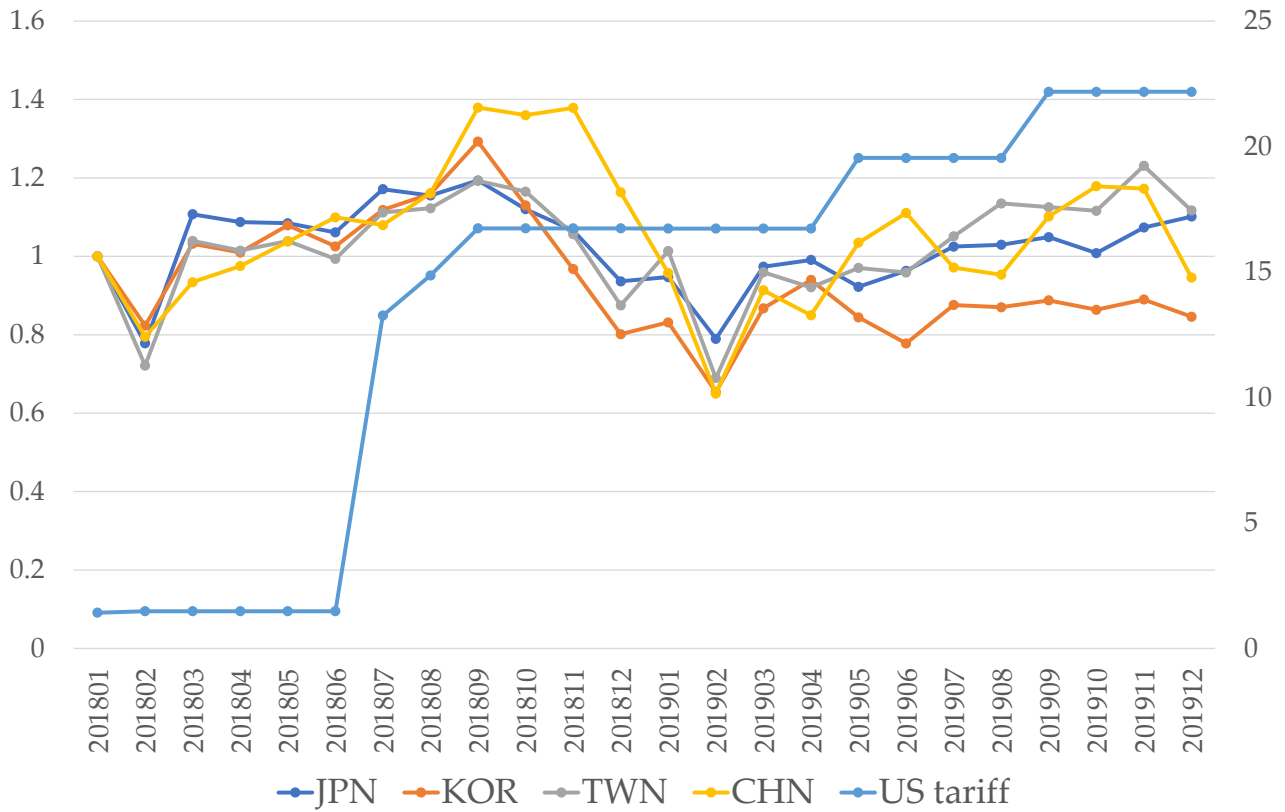
Notes: This table reports the estimation results obtained using the OLS method. ***, **, and * indicate the 1%, 5%, and 10% levels of statistical significance, respectively. Robust standard errors are reported in parentheses. In all specifications, we control for sector fixed effects (defined at the four-digit level in the ISIC). “Import share from JPN” indicates the share of imports from Japan out of total imports. In columns (I) and (II), we include firms in all industries in China. Only firms in machinery industries are examined in columns (III) and (IV). “Drop if export share > 1” indicates whether we drop firms where the share of total exports in total sales exceeds a value of 1.

Figure 1. Monthly Exports from China to the US (Left Axis, January 2018 = 1) and the Simple Average of Tariff Rates in the US on China (Right Axis, %)



Source: Global Trade Atlas

Figure 2. Monthly Machinery Trade and Tariffs



Source: Global Trade Atlas

Notes: This figure shows the monthly exports of machinery parts to China (left axis, January 2018 = 1), the monthly exports of finished machinery products from China to the US, and the simple average of tariff rates in the US on finished machinery products from China (right axis, %).